Reply to Anonymous Referee #1

We thank the reviewer for reviewing our manuscript and providing his/her valuable feedbacks. We have now addressed all of his/her comments and discussed them in the following. The comments were very helpful to identify some unclear issues with regard to the scope, methodologies and conclusions of the paper. We have revised the manuscript to resolve these issues and make our approach and conclusions more clear-cut. Thanks to the reviewer's feedback, the paper is now much improved.

General Comments

- This paper compared different rainfall datasets over East Africa that have 30+ year record, to station data in Ethiopia, Kenya and Tanzania. The authors found that the CHIRPS rainfall and the ORH Tmin/Tmax are the best products to use for long-term climate studies (trend, variability, and extreme indices) and input for climate or hydrological models. While I think this paper is a good start to necessary analysis of daily rainfall products, I have concerns with the lack of independent station data and the narrow scope of the research (results are only regionally relevant, not very generalizable). I think there are ways to work around this problem of data validation in sparse-regions but the authors would need to reframe the paper and consider how to address the greater challenge of evaluating the quality of satellite rainfall in data sparse regions. The authors also need to be more transparent/detailed about their methods (metrics and data sets).

Authors´ response:

- We appreciate acknowledgement that our paper provides a good start for analysing rainfall products. We would rather propose to speak of scarcity of station data, not a general lack of independent station data. We are convinced that this kind of validation of climate data products can only be done at a regional level and indeed we feel that it is impossible to do this at a significantly larger scale than provided here (3 countries in East Africa). We rephrased respective sections (abstract, page 2, lines 7-8), introduction (page 5, lines 19-25) and summary and conclusion (page 21, lines 2-4 and page 22 lines 3- 4 and 10-13) to make this point clearer. In fact, earlier studies with a similar goal of validating climate data (e.g., CHIRPS) products did so based on much more limited data basis in terms of temporal resolution or spatial dimension (e.g., *Duan et al., (2016) and Dembélé and Zwart (2016)*). We also think that our general approach is well generalizable and can and should be used for validating these climate data products in other areas as well.
  We added some explanations in the methodology part (section 3.1, page 9, lines 25-26 and section 3.2, page 10, line 26 to page 11, lines 1-3 and page 13, lines 3-10) to be more transparent and clear.

Specific Comments (Major)

- The focus on daily rainfall is useful/novel as the authors state that this has not been done before. In general this is a regional study that has limited applicability to studies beyond Ethiopia, Tanzania and Kenya, and to the extent that this is generalizable in country in questionable judging from Figure. 1. Not to say that research can't be done in data sparse regions but it has to be framed appropriately, and think that the authors could improve in this respect.

Authors´ response:

- Thanks for pointing out the novelty of our study. It is true that the study is a regional study with a main focus in Ethiopia, Kenya and Tanzania. Following this we modified sections of the paper (e.g., abstract, page 2, lines 7-8), introduction (page 5, lines 19-25) and summary and conclusion (page 21, lines 2-4 and page 22 lines 3- 4 and 10-13)) to emphasize the regional focus – while pointing out that the approach is applicable in other regions, too.

Concerning framing we not only revised sections explaining the regional focus, but also improved the emphasis on the temporal dimension (daily resolution) and the different modes of data validation, going beyond the typical point to pixel comparison (see below).

- In fact, "how to evaluate rainfall and temperature in a data sparse region?" is a good question, although i don't think comparing to a handful of stations that are not independent is necessarily the answer. Major concern is the use of the EMA and GSOD data for evaluation and the conclusion that CHIRPS is the best performing product.

Authors´ response:

- We felt the same and this is why we posed the question – in this case for East Africa. Concerning the number of stations we did our best to get data from more than just a handful of stations: At least for Ethiopia the data set we used represents the most comprehensive to date and the most comprehensive possible (based on a quality controlled dataset from the National Meteorological Agency of Ethiopia). For Kenya and Tanzania data availability is admittedly thinner, partly due to quite restrictive data sharing policies (as explained in the paper), but the available data in our view do allow making the case that we validated the considered data sources at a regional scale. Adding data from two more countries provides additional insights about the accuracy of these data products. The concern with regard to the independency of data is taken up below. Indeed, the inclusion of station data in CHIRPS may raise such concerns. However, the station data used in CHIRPS from Ethiopia, Kenya and Tanzania is mainly a monthly total from a limited number of stations. For the sake of independence it would have been advisable to exclude those stations from our validation data set. However, observed station data were not included consistently in CHIRPS through the study period and even in a single year (e.g., stations used in the first month are not all included in second month). For example, in Ethiopia, in Jan/1983 monthly data from 139 stations are included in CHIRPS and decreased to 132 in Feb/1983. In addition, in Aug/2005 data from 175 stations are included in CHIRPS and decreased to 169 in Dec/2005 (ftp://chg-ftpout.geog.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/diagnostics/). In addition to the publicly available data from Ethiopia, more data from hardcopies had been added to the available stations during a working visit at the National Meteorological Agency of Ethiopia. Therefore, for our validation procedure we used quality-controlled and improved/extended daily data from as many stations as possible. For this validation data set we argued that the "dependency (is) rather weak and indirect" due to the much higher number of stations and the higher temporal resolution. To make this clearer we added a detailed explanation in section 2.2 (data sets) in page 8, lines 19-27 and page 9, lines 1-6.

- I do think that CHIRPS is a very good product (from prior monthly/season scale evaluations and performance in hydrologic models & compared to other remotely sensed data), and it does need to be more carefully evaluated at the daily time-step.

Authors´ response:

- Thanks for pointing out the need for more careful evaluation at a daily time step. This is a very important point and that is why we tried to use the maximum possible validation areas and to find other methods than the typical point-pixel comparison. Using non-aggregated daily data resulted in a comparably weak correlation, but our 3rd method, stations average to area grid-cell average (explained below) produces a good correlation. Therefore, our recommendation for hydrological (or other impact-) modelling is to use the area average (grid-cell average) instead of point/pixel information. We are using the same approach to model a water balance in one of the biggest rivers basins in Ethiopia (area > 62,100 KM^2) and we found a good preliminary model performance of an r2=0.74, NSE=0.73 (final results will submitted to a journal).

- The station data that goes into the different rainfall products needs to be described in the methods/data.

Authors´ response:

- Under each product in section 2.2 (data sets), we added more information about the station data included in each product. For example, in page 7, lines 16-20 and page 8, lines 18-27 and page 9 lines 1-6 for CHIRPS and in page 8 lines 6-10 and lines 12-18 for ORH.

- In addition to the discussion. CHIRPS includes stations from several sources including GTS and GSOD, ARC includes GTS. Please include information on what stations the other products blend in.

Authors´ response:

- Thanks, ORH also used quality-controlled and gap-filled Global Summary of the Day (GSOD). This was already included in the paper (page 8, lines 12-15), but to highlight the use of gap filled GSOD data we modified the text as: *ORH is corrected for temporal inhomogeneity and biases and random errors are omitted through assimilation with quality controlled and gap filled ground station data available at NCDC (https://www.ncdc.noaa.gov/) as a global summery of the day (Chaney et al., 2014)*.

- The authors indicate that GSOD is only used in the CHIRPS monthly totals making the "dependency rather weak and indirect" Seems to me incorporating GSOD would contribute to the strong monthly correlations in Figure 4.

Authors´ response:

- As described in the paper, *"The inclusion of monthly station data can be assumed to improve CHIRPS´ performance compared to other rainfall products"*, so indeed we agree that inclusion of observed monthly totals will contribute to strong correlation on monthly time scale. While the correlated data are not fully independent, even at monthly resolution they are only partially related given that we re-calculated monthly means after quality-controlling daily values and used a much higher number of stations with more data added from hardcopies as explained above and more explanation is given in section 2.2 (data sets) in page 8, lines 19-27 and page 9, lines 1-6.

- From my interpretation of Funk et al. (2015) the GSOD data is included for pentad-totals as well. You may want to ask the data producers to clarify (and then include that information in the data/methods here.

Authors´ response:

- It is true that sparse GSOD/GTS data is also included in pentad-totals globally to produce a preliminary rainfall with a latency of two days and we added this information in section 2.2 (data sets) page 7 lines 16-20 as recommended.

- I* think* Ethiopia NMA stations are included in CHIRPS. Check with the date providers Funk et al. 2015 says: "Addi-tional observations have been provided by national meteorological agencies, primarily in Mexico, Central America, South America, and sub-Saharan Africa".

Authors´ response:

- Yes multiple stations, particularly monthly data, from Ethiopia are included in CHIRPS. But, as explained above, not all stations used in this study are included in CHIRPS and the stations are not consistently used in the development of CHIRPS due to missing values. For example, in Ethiopia, in January 1983 monthly data from 139 stations are used and decreased to 132 Stations in February 1983; in August 2005 about 175 stations are used and decreased to 169 in December 2005. Additionally, after 2005 the numbers of stations used in CHIRPS are declining and finally go to below 10 in 2015. We added more information about this in the revised version as described above in section 2.2 page 8 (lines 19-27) and 9 (lines 1-6).

- apparently ORH also uses GSOD "assimilating quality-controlled and gap-filled Global Summary of the Day (GSOD) in situ measurement"

Authors´ response:

- Yes GSOD data is used in ORH and this is included in the paper (page 8, lines 12-15) to be clearer we modified the text as described above *(ORH is corrected for temporal inhomogeneity and biases and random errors are omitted through assimilation with quality controlled and gap filled ground station data available at NCDC (https://www.ncdc.noaa.gov/) as a global summery of the day (Chaney et al., 2014)).* In addition, we added more information about the type of data included in ORH in page 8 lines 6-10.

- ...what spatial interpolation method do they use?

Authors´ response:

- A bilinear interpolation method is used and this is added in (page 8, lines 4-6) as: ORH is developed by a spatial downscaling of the NCEP–NCAR reanalysis (Kalnay et al., 1996) up to a spatial resolution of 0.1° using a bilinear interpolation. .....

- Evaluation of daily rainfall for trend/variability/extremes/hydro model input is a worthwhile goal. Also not sure if the authors accomplished this given that i have questions about their metrics. I understand that you are comparing to stations but... Daily rainfall intensity: intensity is depth per unit time. How are you getting this when you just have daily totals? And then how does the "intensity" metric differ from what you describe as daily totals? Please include your definition of intensity.

Authors´ response:

- The analysis of trends/variability/extremes will be subject of another paper. We used the term average daily intensity to indicate average daily totals (mm/day) and we changed this into average daily rainfall (mm/day) throughout the manuscript in the revised version.

- Number of wet/dry days: is this just a count that does/does not match the stations? Or are you using something like probability of detection and false alarm rate? These metrics need to be defined in the methods.

Authors´ response:

- It is true that the number of wet/dry days is a count of daily records and we added the definition as recommended in the revised version in section 3.2, page 13 lines 3-9. For your information, we also computed the probability of detection (POD) and false alarm rate (FAR), but it is not included here as it is not common for climate models. Comparing the satellite based rainfall products CHIRPS and ARC2 showed a higher agreement. For example for EthioShed1 we found a POD of 0.83, 0.84, and 0.49 and FAR of 0.12, 0.1, and 0.24 for ARC2, CHIRPS and ORH, respectively.

- I can't really tell what you did to come up with the results on page 13. Not obvious what "point to area-grid-cell" average means. I gather that its the average over the polygons shown in Figure 1, but this needs more explanation in the methods.

Authors´ response:

- Yes it is true "area-grid-cell average" means the basin/polygon average and we added an explanation in section 3.2 (methodology) page 10 (line 26) – page 11 (lines 1-3) as recommended.

- Where do these polygons come from? Is there a reason why this level of basin was used to define the watersheds for a country?

Authors´ response:

- The polygons are basins retrieved from the global river basins available at the WaterBase hosted by the United Nations University (UNU-INWEH: *http://www.waterbase.org*) and we add few lines about the polygons and the data source in the revised version in section 3.1, page 9 (lines 25-26) – page 10 (line 1).

- Since you're not comparing to hydrological/ streamflow data why not just average from 0.05 to 0.25 degree – essentially producing the same results as what you discuss with the coarser CHIRPS data?

Authors´ response:

- That is possible, but our objective is to find finer spatial resolutions that can be used later for hydrological and climate modelling in areas of the region with no ground observation. As we showed in section 4.2, page 16 (lines 25-26) – page 17 (lines 1-2), the improved version of CHIRPS (0.05 degree) is more accurate than the coarser resolution of CHIRPS (0.25 degree).

Specific comments (Minor)

- Additional information on how the data is produced should help explain your results (e.g. why is point to area-average best, does this have to do with the interpolation schemes that ARC and CHIRPS and the other product use?

Authors´ response:

- This is not because of the interpolation schemes that the products used but due to the method we used to compare the products. Compared to the point to pixel method, area averaging produces higher correlation and lower errors. During area averaging extremely high rainfall events obtained for a location from the various data products are levelled off by averaging and this makes the product much more accurate. In most of the rainfall products, including CHIRPS, there are occasionally higher daily rainfall values recorded and the averaging removes those extremes, which are much higher than the observed data in the area. We included this information in the revised version in page 15 lines 3-7.

- Do CHIRPS results improve at 0.25deg because that is its original resolution, before being downcaled to 0.05deg with the CHPclim? This kind information will be useful for the other products as well.

Authors´ response:

- NO, there seems to be a misunderstanding. As we showed in section 4.2, page 16 (lines 25-26) – page 17 (lines 1-2), the higher resolution of CHIRPS (0.05 degree) showed an improvement in correlation with station data by up to 3.2% compared to the coarse resolution of CHIRPS (0.25 degree).

- Is only a historic record needed for env. Management? ORH isn't updated regularly (2012?) This should be clear in the paper, pls include in methods.

Authors´ response:

- Yes we agree not only historical records are required. It is true that ORH is not updated regularly (last update in February 2016) and the global data is available from 1901-2012 at different resolutions. To make this clearer we added few lines and its application, with a list of publications, in environmental management in page 8, lines 3-18.

- Meanwhile, ARC & CHIRPS are updated regularly. It will help contextualize the metrics if you discuss the products strengths and weaknesses more with some example of an environmental management application that they might be used for. I am sure there are some that would benefit from ORH long record, or ARC's 1-day latency.

Authors´ response:

- Thank you very much for this remark and proposal. We included the strength and weakness of the products in terms of resolution, length of time period and progress (regular updating) in the data set (section 2.2). For ARC2, for example, we modified the text in page 7 lines 9-11 as: *The data set is updated regularly (last update March 2018) and it is available at a spatial resolution of 0.1° covering the period of 1983–2018.*

- If you are including OHR why not include what they use routinely in the Africa Flood and Drought monitor? 3B42RT...

Authors´ response:

- We agree that the 3B42RT is a very good rainfall product and lots of papers are already available, but for our project we are interested in products with an observation period of more than 30 years, which is not the case for 3B42RT.

- how does blending datasets impact the application to environmental management? With respect to hydrologic modeling GLDAS (Rodell et al. 2004) uses ORH/Princeton+other, Africa flood and drought monitor (Sheffield et al. 2014) uses ORH/TRMM-RT, FLDAS (McNally et al. 2017) uses CHIRPS. How does all this relate to the climate models?

Authors´ response:

- This is a very good point and the products have shown a positive impact in environmental management in data sparse regions such as Africa. Compared to climate models, satellite based rainfall products, based on our findings, show higher accuracy (see figure 4) and we believe that satellite based products can be more accurate for environmental management than output from climate models. The role of data blending, including the recommended papers, in environmental management are highlighted for each data set (section 2.2) and a text is added to highlight the role of satellite-station data blending techniques in page 14, lines 14-16 by giving an example of CHIRP and CHIRPS. .

- intro was vague and too focused on data scarcity - we have lots of data (models, remote sensing, some in situ)...just not lots of dense rainfall stations.

Authors´ response:

- Thank you very much; we modified the introduction by removing some sections in the revised version, and we pointed out that data scarcity mainly refers to station data in pages 3 (lines 21-26) - 4 (lines 1-3).

- …there are lots of datasets to get temperature (e.g. MERRA-2, CFS-R). Why weren't these included?

Authors´ response:

- We screened multiple data sources for temperature and our selection is based on their spatial resolution, length of time period (> 30 year) and recommendations from previous papers.

- Technical corrections > fix citation (also 2017): Kimani, M., Hoedjes, J. and Su, Z.: Uncertainty Assessments of Satellite Derived Rainfall Products, , 15. doi:10.20944/preprints201611.0019.v1, 2016. Don't cite the pre-print use this one: Kimani, Margaret Wambui, Joost CB Hoedjes, and Zhongbo Su. "An Assessment of Satellite-Derived Rainfall Products Relative to Ground Observations over East Africa." Remote Sensing 9.5 (2017): 430.

Authors´ response:

- Thank you very much and this is fixed in the revised version.

- Typo RFE pg 6...its RFE Rainfall Estimation Version 2 (REF 2.0) (Novella et al., 2013)

Authors´ response:

- Thank you very much and this is fixed in the revised version.

References:

Chaney, N. W., Sheffield, J., Villarini, G., Wood, E. F., Chaney, N. W., Sheffield, J., Villarini, G. and Wood, E. F.: 20 Development of a High-Resolution Gridded Daily Meteorological Dataset over Sub-Saharan Africa: Spatial Analysis of Trends in Climate Extremes, Httpdxdoiorg101175JCLI--13-004231 [online] Available from: http://journals.ametsoc.org/doi/abs/10.1175/JCLI-D-13-00423.1 (Accessed 30 November 2016), 2014.

Dembélé, M. and Zwart, S. J.: Evaluation and comparison of satellite-based rainfall products in Burkina Faso, West Africa, Int. J. Remote Sens., 37(17), 3995–4014, doi:10.1080/01431161.2016.1207258, 2016.

Duan, Z., Liu, J., Tuo, Y., Chiogna, G. and Disse, M.: Evaluation of eight high spatial resolution gridded precipitation products in Adige Basin (Italy) at multiple temporal and spatial scales, Sci. Total Environ., 573, 10 1536–1553, doi:10.1016/j.scitotenv.2016.08.213, 2016.

Reply to Anonymous Referee #2

We thank the reviewer for reviewing our manuscript and providing his/her valuable feedbacks. We have now addressed all of his/her comments and discussed them in the following. The comments were very helpful to identify some unclear issues with regard to the scope, methodologies and conclusions of the paper. We have revised the manuscript to resolve these issues and make our approach and conclusions more clear-cut. Thanks to the reviewer's feedback, the paper is now much improved.

General comments

- This paper is specifically validating the quality of three climatic variables coming from different satellites data-streams and models using scientifically proven quality validation methodologies. The three include rainfall, maximum temperature and minimum temperature. Being a research that has been done for the first time that I know of, the paper unravels the different quality of each of these datasets and with evidence provide great knowledge of which is the best among the 6 datasets for each variable. If further validate the same dataset with observed rainfall and satellite from weather stations. Though not conclusive, through this research, one can relate that the CHIRPS dataset is better for rainfall analysis in specific areas which have complex topography with a case study in three East African countries. While the ORH dataset works best for the Tmax/ Tmin variable. The paper specifically highlight the methods used and why and how each one is best.
  East Africa being a complex region of climate analysis. The paper seems to have limited itself to specific sites which might not fully represent the entire region. Despite having fewer observed data the sample areas of interest might limit the imagination of the complexity of the region.

Authors´ response:

- Thanks for pointing out/acknowledging the difficulties in performing this kind of studies. Indeed the observed data is very limited in terms of spatial coverage and length of time period. In addition, getting daily data from the meteorological agencies is not easy, particularly from Kenya and Tanzania due to their data sharing policy. Therefore, for the purpose of validation we used almost all the available stations (210), particularly in Ethiopia, with an elevation, as given in Table 1, from 400-2510 and average elevation of the validation areas from 520-2830 meters. The included station data from Kenya and Tanzania range in altitude from 1097 to 2328 masl. Therefore, based on the stations at different elevations we conclude that our data set (which is the most comprehensive for East Africa to date) reasonably represents the study area even in those parts were no ground observations are available.

- CHIRPS products seemed to work well in some areas while at the same time came in second in other areas. The author should try and indicate by what percentage in all the analysis done was CHIRPS top and if the percentage is worth representing the region as the best dataset.

Authors´ response:

- We concluded CHIRPS to be the best product for rainfall based on the overall analysis (daily-monthly), the multiple statistics used (Table 3 and Figure 4 and 5) and the result of the analysis of rainfall characteristics (Table 4, see below). Table 4 is added in the revised version page 15 and the text in lines 21-24 is modified as: *On average, over the 21 validation areas, CHIRPS captures well the number of wet days (-0.17 % deviation), average duration of wet (-13.4 % deviation) and dry periods (-*

17.6 % deviation), total rainfall (-4.5 % deviation), average amount of wet periods (-17 % deviation), and average daily rainfall (-7.7 % deviation) (Table 4). The values in the bracket show the percentage deviation from the observed data. As we are using multiple statistical methods and multiple time scales and metrics, providing one general percentage for a product might be not appropriate.

Specific comments

- In page 9 of the document the author mentions that "The quality of selected stations was checked and extremely high rainfall records during dry seasons were excluded." Through this statement it is not clear what is considered as a dry season and the reason for exclusion of such rainfall dataset remains hanging. Also in consideration of the same, extreme event such as flash floods may be recorded in a single days' rainfall.

Authors´ response:

- During quality control few data were removed with extremely higher rainfall events such as >480 mm/day preceding and following dry days. We have done the quality control with the meteorology-experts in the field (colleagues from National Meteorological Agency, Ethiopia) and these data had been identified as error in inputting the data. This information is included in the revised manuscript in page 10, line 9-11.

- A few questions to be asked are; Could the x,y decimal places affect the location of a given station ending up reporting a value for a wrong location? For example a station reading of 36.123456, -1.123456 might fall at a different location compared to a reading of 36.123, -1.123. In this reference were the station locations validated?

Authors´ response:

- Good point: It is well conceivable that stations are falsely located in the next grid box of the product especially if you have a product with very high resolution such as CHIRPS and ARC2. For this reason we used all available station information and the extracted data is validated. This can be a problem if you are comparing station to pixel. But if you are using the station average to area grid cell average the change from 36.123456, -1.123456 to 36.123, -1.123 might not be a problem if they are located inside the validation area as you are taking the average.

- From this paper it is also not clear what the following terms refer to; Wet days, duration of wet days and average amount of wet periods this might be confusing since they all are represented by one unit which is days. For example, when we talk about wet days we say 10 days. If we talk about duration of wet days do we still say 10 days? The same applies to the average amount of wet periods.

Authors´ response:

- Thank you very much for pointing out this issue. The unit for number of wet days (count of wet days in a year) is days/year, for average duration of wet periods (the number consecutive wet days) is days and for average amount of wet periods is mm. The full description of the rainfall characteristics with their units is included in the methodology part (section 3.2, page 13, lines 3-9) of the revised version and the results of the rainfall characteristics are provided in Table 4.

- From the paper it is very clear that the author highlights CHIRPS as the best rainfall product while ORH as the best temperature product. CHIRPS comes out better than the rest based on the characteristics described by the author in page 14 but the author has not conclusively stated by how much is CHIRPS better than all this other products if you compare all the statistical analysis done. The Author has only highlighted that "In general, the observed rainfall characteristics are well captured by CHIRPS compared to CHIRP, ARC2, ORH, RCM, and RCMs."

Authors´ response:

- Thank you very much and we provide a table in page 15, lines 21-24 with a summary statistics of the rainfall characteristics, with a percentage deviation from the observation, as given below (Table 4) in the revised version and the text in page 16 lines 10-13 is modified as: *In general, the observed rainfall characteristics are well captured by CHIRPS, with a percentage difference from the observation of -0.17 % to -17.6 % for number of wet days and duration of dry periods, respectively, compared to CHIRP, ARC2, ORH, RCM, and RCMs (Table 4).*

- While at the same time pointed out areas that ARC2 has performed better that CHIRPS and CHIRP. Regarding the above, in some instances such as EthioShed4 the CHIRP and CHIRPS have equal R squared while in some areas ARC2 came on top. Through the analysis of all the Sheds analysed what percentage of CHIRPS compared to the rest of the datasets was better.

Authors´ response:

- Yes it is true that both ARC2 and CHIRP have shown higher R squared, considering the biases and errors, in 2 and CHIRPS in 17 of the 21 validation areas. However, in terms of capturing the daily rainfall characteristics (Table 4) ARC2 showed higher deviations compared to CHIRPS. In EthioShed4, CHIRP and CHIRPS have an equal R squared, but in terms of biases CHIRP showed higher biases (data points below and above the regression line) compared to CHIRPS (most of the data points lie in the regression line) as shown in figure 4. We added an explanation in page 14 lines 13-14 in the revised version.

- Still in line with that there are some areas where all the R squared were between 0.13 and 0.55, is it possible to elaborate on why such cases occur? Is it the methodology used to model the datasets that limits the correlation with the station data?

Authors´ response:

- The small R squared values were mainly computed for the regional climate models (RCMs). Compared to the satellite based rainfall products (which already include ground observed data), RCMs have a coarse spatial resolution (~ 50 km) and during the downscaling process of the global climate models they include less local information such as topographical features, which makes them weak in synthesising local daily rainfall, particularly in topographically very complex regions.

- Another question of concern is what explains the equal value for CHIRP and CHIRPS as portrayed in EthioShed4?

Authors´ response:

- In EthioShed4 it is true that R square value is the same, but if you see the distribution of the data above and below the regression line there is a difference, which is explained as a bias (over- or underestimation). To compare both products it is also good to see figure 5 (Taylor-diagram), which shows the correlation and standard deviation of each product on monthly time scale. Therefore, in addition to the bias shown in figure 4, figure 5 also shows a deviation between CHIRPS (with slightly better correlation and standard deviation on monthly time scale similar to figure 4) and CHIRP.

- In the introduction the paper highlights CHIRPS as a dataset that has both station and satellite data in it. Might this explain the high correlation?

Authors´ response:

- As we explained in the methodology and discussion part, station data are included in CHIRPS, ARC2 and ORH. But compared to ARC2 and ORH, a larger number of stations are included in CHIRPS. Therefore, on a monthly time scale, the high correlation can be true due to the inclusion of monthly station data in the development of CHIPRS. In the revised version we include a section in page 8 lines 19-27 and page 9 lines 1-6 in the data sets section highlighting the stations included in CHIRPS (see also replies to reviewer #1).

- Are the same stations in CHIRPS used to validate the CHIRPS product?

Authors´ response:

- Yes – but due to different data processing and inconsistent use of station data in CHIRPS, the data included there are not fully congruent to the station data we used in the correlation. Multiple stations, particularly monthly data, from Ethiopia are included in CHIRPS as shown in table one and discussed in the discussion part. But, not all stations used in this study are included and the stations are not consistently used in the development of CHIRPS due to missing values. For example, in Ethiopia, in Jan/1983 monthly data from 139 stations are included and decreased to 132 in Feb/1983. In addition, in Aug/2005 monthly data from 175 stations are included and decreased to 169 in Dec/2005 (ftp://chg-ftpout.geog.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/diagnostics/), which shows the inconsistency in the inclusion of the stations. We added more information in section 2.2 (data sets) in page 8 lines 19-27 and page 9 lines 1-6

In conclusion to the specific comments.

- The paper is very clear on how the validation is done. However, more can be done to ensure that these products are regarded as the best products as indicated by the author.

Authors´ response:

- Thank you very much for the comment and we consider your comments and we added a summary statistics table (e.g., Table 4) as mentioned above in the revised version.

- The paper currently is validating the products for areas with low observed dataset. Perhaps, the author can use historical analysis as a means of validation too. Also, an elaborate point of validation would be to highlight how the non-blended datasets such as CHIRP is performing compared to observed station data in regions that have well established network of weather stations such as the developed countries. Then further, validating the CHIRP against the CHIRPS. This will basically ensure less redundancy.

Authors´ response:

- Thank you very much and we added an explanation about the role of the station blending technique in page 14 line 14-16 in the revised version as recommended. Concerning the use of historic data: we did that to the extent possible, limited by the lengths of available time series, but in general using 30-year datasets. However, it would go beyond the scope of this paper to extend the analysis to further (developed) countries and regions. Adding even more data, figures and respective discussions to the paper does not seem feasible to us. We definitely agree that it would be worthwhile to use the same approach of validating climate data products in other countries and regions. It is well conceivable that obtained results in terms of best products might look different, which could be due to various factors: higher spatial resolution, better general data quality, higher homogeneity of the region in terms of topography etc. To conclude: we feel that extensions to further regions and ultimately to the global scale requires (a) separate study/studies.

Technical comments

- In page 7, the Dekadal should come after pentadal since the former represents 10 days and the later represents 5 days.

Authors´ response:

- Thank you very much and we fixed this in the revised version.

- In page 13, 17 is numerical while three and one are text – you might want to use either for all.

Authors´ response:

- It is very common to convert numbers <10 to text, but not larger numbers. This will be checked with editorial policies of HESS.

- In Page 20, it is indicated that "The products are available with higher spatial and temporal resolution and for longer periods." – doesn't longer periods mean the same as temporal resolution?

Authors´ response:

- No, the terms have different meanings. Temporal resolution is used to indicate the time scale such as daily, dekadal and monthly; longer periods refers to the length of the time period/series such 30 or >30 years.

Table 4: Summary of daily rainfall characteristics retrieved from multiple rainfall products and averaged over the validation areas of Ethiopia, Kenya and Tanzania. Values in brackets give the deviation from the observed value (%). The value which comes closest to the observed value is highlighted in bold.

Rainfall characteristics	Obs.	ARC2	CHIRP	CHIRPS	ORH	HadGEM2	MPI	GFDL	RCMs
Number of wet days (days/year)	189.58	162.98 (-15.1)	351.06 (59.7)	**189.26** (-0.17)	192.14 (1.34)	205.08 (7.85)	243.55 (24.92)	210.42 (10.42)	299.36 (44.9)
Average duration of wet periods (days)	5.86	4.78 (-20)	167.96 (186)	**5.13** (-13.4)	3.02 (-64)	11.70 (66.5)	12.17 (69.9)	9.37 (46)	21.36 (113.9)
Total amount of precipitation (mm/year)	953.63	671.62 (-34.7)	**980.24** (2.75)	912.0 (-4.5)	1027.02 (7.41)	841.73 (-12.5)	1055.7 (10.2)	1253.38 (27.2)	1068.6 (11.4)
Average amount of wet periods (mm)	30.20	20.56 (-38)	498.43 (177)	**25.46** (-17)	15.64 (-63.5)	50.12 (49.6)	55.45 (59)	59.64 (65.6)	78.88 (89.3)
Average duration of dry periods (days)	5.37	6.01 (11.3)	1.53 (-111.3)	4.5 (-17.6)	2.55 (-71.31)	6.91 (25.04)	**5.67** (5.4)	6.55 (19.8)	3.55 (-41)
Average daily precipitation (mm/day)	5.28	4.16 (-23.8)	2.78 (-62)	4.88 (-7.7)	**5.4** (2.3)	3.88 (-31.5)	4.19 (-22.8)	5.69 (7.6)	3.48 (-41)

Reference:

Jebari, S., Berndtsson, R., and Bahri, A., (2012). Soil erosion estimation based on rainfall disaggregation. J. Hydrology. 436-437; 102–110.

Evaluation of Multiple Climate Data Sources for Managing Environmental Resources in East Africa

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Abstract. Managing environmental resources under conditions of climate change and extreme climate events remains among the most challenging research tasks in the field of sustainable development. A particular challenge in many regions such as East Africa is often the lack of sufficiently long-term and spatially representative observed climate data. To overcome this data challenge we used a combination of accessible data sources based on station data, earth observation by remote sensing, and regional climate models. The accuracy of the Africa Rainfall Climatology version 2 (ARC2), Climate Hazards Group InfraRed Precipitation (CHIRP), CHIRP with Station data (CHIRPS), Observational-Reanalysis hybrid (ORH), and Regional Climate Models (RCMs) are evaluated against station data obtained from the respective national weather services and international databases. We did so by relating point to pixel, point to area grid cell average, and stations average to area grid cell average over 21 regions of East Africa: 17 in Ethiopia, two in Kenya and two in Tanzania. We found that the latter method provides better correlation and significantly reduces biases and errors. The correlations were analyzed at daily, dekadal (10 days), and monthly resolution for rainfall and maximum and minimum temperature (T-max and T-min) covering the period of 1983–2005. At daily time scale, CHIRPS, followed by ARC2 and CHIRP are the best performing rainfall products compared to ORH, RCM, and RCMS. CHIRPS captures well the daily rainfall characteristics such as average ~~rainfall intensity~~daily rainfall, amount of wet ~~days~~periods, and total rainfall. Compared to CHIRPS, ARC2 showed higher underestimation of the total ~~rainfall~~ (-30 %) and daily ~~intensity~~ (-14 %) rainfall. CHIRP on the other hand, showed higher

underestimation of the average daily rainfall~~intensity~~ (-53 %) and duration of dry ~~days~~ periods (-29 %). Overall, the evaluation revealed that in terms of multiple statistical measures used on daily, dekadal, and monthly time scale, CHIRPS, CHIRP, and ARC2 are the best performing rainfall products while ORH, individual RCM, and RCMs are the least performing products.

For T-max and T-min, ORH was identified as the most suitable product compared to RCM and RCMs. Our results indicate that CHIRPS (rainfall) and ORH (T-max and T-min), with higher spatial resolution, should be the preferential data sources to be used for climate change and hydrological studies in areas of East Africa where station data are not accessible.

1. Introduction

In Sub Saharan Africa (SSA) about 80 % of people living in poverty will continue to depend on the agriculture sector as their major income sources under the continuing global change (Dixon et al., 2001; IFPRI, 2009). Unlike in other regions of the world, agricultural activities in SSA are marked by low production mainly due to poor natural resource management, rainfall amount and variability, economy, and technologies. According to IFPRI (2009), reducing poverty in SSA is becoming more challenging due to rapid population growth and associated decline in the quality and availability of environmental resources (e.g. water and soil). Additionally, food security and livelihoods of people are threatened by the direct impacts of change in climate such as increasing frequency of extreme events and weather variability impacts on the production and productivity of agricultural lands (Malo et al., 2012). In general, the impact of climate change in Africa ranges from social and economic to health, water, and food security, which is a threat to the lives of Africans (Urama and Ozor, 2010; Gan et al., 2016).

These outlined challenges hold in particular for the eastern parts of SSA, including Ethiopia, Kenya, and Tanzania. The population (>80 %) mainly depend on agriculture for their livelihood in this region and agriculture-based income contributes 40 % to the country's Gross Domestic Product (GDP) (FAO, 2014). Extreme climate events such as recurring droughts and floods have a tremendous impact on the socio-economy of the region. Devastating droughts in SSA linked to the high variability (seasonal and inter-annual) of rainfall (Sheffield et al., 2013) are projected to increase in frequency (IPCC, 2007, 2014; Niang et al., 2014). In addition to the projected impact, the region is already facing significant food security issues and natural resource-based clashes (UNEP, 2011; World Bank, 2012).

The impacts of future climate change in East Africa vary from region to region. In order to understand the impacts of future climate at the regional and local scale, ground station data with high spatial and temporal resolution is crucial. Regions with poor ground observation are highly vulnerable to climate threats (Wilby and Yu, 2013), which holds particularly for developing countries. In Africa, high quality climate data from meteorological field stations are scarce and inconsistencies exist between other data products largely due to a limited number of ground stations, merging and interpolation methods

(Huffman et al., 2009; Nikulin et al., 2012; Sylla et al., 2013), limited time resolution, and limited documentation quality. In addition, climate data with high temporal and spatial resolution, even if collected by the national meteorological agencies, are often not available due to data sharing policies. With advancements of technologies and research activities, a number of climate data products from different sources (remote sensing, climate model, and reanalysis) have been produced over the last decades that can fill the data gap particularly for drought-prone regions (Gan et al., 2016) and can be used for hydrological and climate change studies.

Several satellite-based rainfall estimates have been developed over the last decades (Sapiano and Arkin, 2009; Zambrano-Bigiarini et al., 2016). In Africa, a list of rainfall and temperature products are available that can be used for climate change studies such as the African Rainfall Climatology Version 2.0 (ARC2) from the Climate Prediction Center (CPC) of the National Oceanic and Atmospheric Administration (NOAA) with a spatial resolution of 0.1º (Novella et al., 2013) and Climate Hazards Group InfraRed Precipitation (CHIRP) and CHIRP with Station data (CHIRPS) from the Climate Hazard Group (CHG) with a spatial resolution of 0.05º (Funk et al., 2015). ~~In addition, the Multi-Source Weighted-Ensemble Precipitation (MSWEP) (Beck et al., 2016), Tropical Applications of Meteorology using Satellite and ground-based observations (TAMSAT) (Tarnavsky et al., 2014), and TAMSAT African Rainfall Climatology And Time series (TARCAT) (Maidment et al., 2014) are available at varying resolutions and for longer periods.~~

As another source of climate information, climate model-derived data are suitable tools for assessing climate variability and change. The current resolution of Global Climate Models (GCMs) is too coarse (about 100–250 km) for regional and local scale climate studies. Regional Climate Models (RCMs) produced from dynamically downscaled GCMs provide spatial resolutions that suit end-users (Sun et al., 2006). However, downscaling of climate information from GCMs to assess the impact of climate change on environmental resources at regional or smaller scale has only recently been performed, e.g. as dynamical downscaling within the CORDEX community (CORDEX-Africa, see e.g. Abiodun et al. (2016)). In Africa (CORDEX-Africa domain) the spatial resolution of RCMs is available at about 0.44º (~50 km) and at varying temporal resolutions. In East Africa, a number of studies have been done with the applications of RCMs for climate studies (Anyah and Semazzi, 2006, 2007; Diro et al., 2011; Endris et al., 2013; Segele et al., 2009). ~~According to a recent study (Endris et al., 2015) on the performance of RCMs in East Africa, the Rossby Center Regional Atmospheric Model (RCA) and COnsortium for Small-scale MOdelling (COSMO) Climate Limited Area Modeling (COSMO-CLM or CCLM) models driven by HadGEM2-ES, MPI-ESM-LR, and GFDL-ESM2M were found suitable for climate and climate change studies.~~

Before being used as input to different climate or hydrological models, climate data products need to be evaluated against field-based meteorological stations. For studying climate change and climate extremes data with high accuracy and from long periods (> 30 years) are required. In addition, current hydrological (e.g. Soil-Water Assessment Tool) and climate models (e.g. Statistical Downscaling Model) require daily time series of rainfall and temperature covering long periods. Considering these requirements, concerning lengths of time series and temporal resolution on the one hand and the limited availability of station data on the other hand, it is not surprising that comprehensive evaluations of climate data products, particularly on daily time scale, are not available for East Africa to the best of our knowledge. However, few studies are available based on monthly gridded data (e.g., Cattani et al., 2016; Kimani et al., 2017)~~(e.g., Cattani et al., 2016; Kimani et al., 2016)~~, for limited time periods. Moreover, Kimani et al. (2017)~~Kimani et al. (2016)~~ only considered CHIRPS, whereas in this study we aim at a comparison of different data sources.

Therefore, this study aims at comparing and evaluating the available climate data products for ~~East Africa~~Ethiopia, Kenya, and Tanzania at daily, and extended to dekadal (10 days) and monthly resolution against station data using the most widely applied and accepted statistical and graphical evaluation methods. Results of our study will help overcome the data scarcity in the study area, in terms of spatial coverage and temporal resolution gaps of daily, dekadal, and monthly climate data products that can be used for hydrological and climate change and impact studies at watershed or regional scale. In addition, the data sets can be used for local and regional climate projections using climate models such as Statistical DownScaling Model (SDSM) (Wilby and Dawson, 2004).

2. Study area and Data

2.1 Study region

The study focuses on the evaluation of daily, dekadal, and monthly climate data sources for regions of East Africa, particularly Ethiopia, Kenya, and Tanzania (Fig. 1). The region is divided by the Great Rift Valley and is topographically one of the most diverse and complex parts of Africa, characterized by multiple rainfall regimes. Generally, the rainfall cycle (climatological annual cycle) in East Africa is linked to the position changes of the Inter-Tropical Convergence Zone (ITCZ) (Endris et al., 2013). Variability in the rainfall patterns in this region is partly induced by local factors such as heterogeneity of land surface and complex topography and their interaction with global climate forcing systems. Countries of the region face similar weather and climate variabilities (spatial and temporal variabilities) and increasing temperature and decreasing precipitation trends (Pricope et al., 2013). In addition, all East African countries face similar issues such as frequent droughts, floods, poverty, and lack of clean and adequate water supply. The conditions can worsen in the near future due to climate change; therefore, sustainable adaptation and mitigation strategies are required, which rely on advanced climate and hydrological models and the respective data inputs.

2.2 Data sets

The reference data sets used for evaluation of multiple data products in this study are based on daily rainfall, maximum temperature (T-max), and minimum temperature (T-min) derived from 332 rain gauges and synoptic stations. Station data for Ethiopia was provided by the National Meteorological Agency (NMA) of Ethiopia for the period 1954–2016. The daily data provided by NMA were carefully and extensively checked for its quality and some missing data were infilled from hardcopies. For Kenya and Tanzania, the global summary of the day available at the National Climate Data Center (NCDC) (https://www.ncdc.noaa.gov/) is used. For evaluation, satellite-based rainfall estimates, Observational-Reanalysis Hybrid (ORH), and historical period of Regional Climate Models (RCMs) driven by Global Climate Models (GCMs) are compared against field-based meteorological stations. The three satellite-based rainfall estimates are the African Rainfall Climatology Version 2.0 (ARC2) (Novella et al., 2013), the Climate Hazards Group InfraRed Precipitation (CHIRP) and CHIRP with Station data version 2 (CHIRPS) (Funk et al., 2015).

ARC2 is the second version of the ARC and is compatible with the algorithm of the Rainfall Estimation Version 2 (R~~E~~FE 2.0) (Novella et al., 2013). The product is a composite of three hourly geostationary Infrared (IR) data, which makes it different from R~~E~~FE, centered over Africa provided by the European Organization for the Exploitation of Meteorological Satellites (EUMETSAT) and quality controlled daily rainfall records acquired from the Global Telecommunication System (GTS) gauges. ARC2 is consistent with the historical data sets of the Climate Prediction Center Merged Analysis of Precipitation (CMAP) and Global Precipitation Climatology Project (GPCP) (Novella et al., 2013). The ~~gridded~~ data set is updated regularly (last update March 2018) and it is ~~is~~ available at a spatial resolution of 0.1° covering the period of 1983–~~2016~~2018.

CHIRPS is a semi-global rainfall product designed for drought monitoring and global environmental changes (Funk et al., 2015). The product provides daily, pentadal, dekadal, ~~pentads,~~ and monthly data at a 0.5° spatial resolution available at Climate Hazards Group (CHG ftp://ftp.chg.ucsb.edu/pub/org/chg/products). CHIRPS combines a 0.05° resolution of satellite images and data from ground stations to form a gridded rainfall time series. Stations data (see also below) are used to produce a preliminary two day and final (about three weeks) rainfall product by blending data from sparsely located GTS gauges with pentadal rainfall estimates retrieved from the Cold Cloud Duration (CCD) and available monthly and pentadal station data with monthly and pentadal rainfall estimates retrieved from the CCD, respectively. The development process of CHIRPS includes the 0.05° monthly precipitation climatology (CHPclim), satellite only Climate Hazards Group InfraRed Precipitation (CHIRP) and station blending techniques. The second version of CHIRPS, which is updated regularly (last update February 2018), provides an improved daily rainfall time series (1981–~~2017~~2018) with a spatial resolution of 0.05° ranging from 50ºS to 50ºN (and all longitudes) (Funk et al., 2015). The development process of CHIRPS and its application in drought monitoring in Africa (e.g. Ethiopia) is explained in detail by Funk et al. (2015). CHIRPS is not only used for drought monitoring, but also for other global environmental applications (Zambrano-Bigiarini et al., 2016), water resource management, and climate dynamics (Ceccherini et al., 2015; Deblauwe et al., 2016).

ORH is a global (Sheffield et al., 2006) and regional (Northern/West/East Africa) (Chaney et al., 2014) three-hourly, daily, and monthly meteorological data set covering the period between 1901–2012. ORH is developed by a spatial downscaling of the NCEP–NCAR reanalysis (Kalnay et al., 1996) up to a spatial resolution of 0.1° using a bilinear interpolation. ORH merges multiple data products such as the NASA Langley Surface Radiation Budget (SRB), the monthly temperature data from the University of East Anglia Climate Research Unit (CRU)~~–~~, Tropical Rainfall Measuring Mission Multi-satellite Precipitation Analysis (TMPA~~-~~) (Huffman et al., 2007) and other observational based rainfall products (Chaney et al., 2014). The spatial downscaling of ORH is done with the inclusion of changes in elevation and it is evaluated against ground stations (global summary of the day) available at the US National Climatic Data Center (NCDC). ORH is corrected for temporal inhomogeneity and biases and random errors are omitted through assimilation with quality controlled and gap filled ground station data available at NCDC (https://www.ncdc.noaa.gov/) as a global summery of the day ~~observations~~ (Chaney et al., 2014). This data is freely available from the Terrestrial Hydrology Research Group, University of Princeton (http://hydrology.princeton.edu). Even though ORH is not updated regularly (last update February 2016), it has been widely used in climate and hydrological studies ~~-~~(e.g., Troy et al., 2011; Wang et al., 2011; Demaria et al., 2012; Sheffield et al., 2014)

Compared to the other rainfall products, monthly ground station data from Ethiopia, Kenya, and Tanzania are included in CHIRPS. Evaluating CHIRPS based on ground station data might thus raise concerns about the independence of data. However, not all stations used in this study are included in CHIRPS and the stations are not consistently used in the development process of CHIRPS. In addition, the station data used in CHIRPS is mainly a monthly total from a limited number of stations. For example, in Ethiopia, in January 1983 monthly data from 139 stations are used and decreased to 132 Stations in February 1983; in August 2005 about 175 stations are used and decreased to 169 in December 2005. Additionally, after 2005 the numbers of stations used in CHIRPS are declining and finally go to below 10 in 2015. In Kenya and Tanzania, moreover, monthly station data from 142 and

171 are included in CHIRPS in January 1983 and decrease to 62 and 55 stations in December 2005, respectively (ftp://chg-ftpout.geog.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/diagnostics/). Besides the difference in temporal resolution (monthly vs. daily) and the number of stations between station data included in CHIRPS and the validation data set, the latter was independent in the sense that we used original data provided by NMA (Ethiopia) which were quality-controlled and extended by adding data from hard copies.

Historical data (control model runs) of the CORDEX RCMs are also used as a potential source for rainfall, T-max, and T-min data. RCMs are climate models with a higher spatial resolution compared to GCMs. The driving data of RCMs are derived from GCMs or reanalysis data and can include greenhouse gases (GHG) and aerosol forcing. Compared to GCMs, RCMs considers local factors such as complex topography and land cover inhomogeneity in a physically based manner (IPCC, 2007). In Africa, dynamical downscaling was performed in a large effort within the CORDEX community (CORDEX-Africa). Within CORDEX-Africa the continent's climate was dynamically modelled by an international consortium, providing a spatial resolution of about 50 km. According to the IPCC report (2007), RCMs can be used for wide range applications such as climate change studies. Following the recommendation of Endris et al. (2015), the historical data derived from two CORDEX RCMs, RCA (Samuelsson et al., 2011), and COSMO-CLM or CCLM (Baldauf et al., 2011), driven by HadGEM2-ES (MOHC, United Kingdom), MPI-ESM-LR (MPI, Germany), and GFDL-ESM2M (NOAA/GFDL, United States) are used. Rainfall, T-max, and T-min products of both RCMs are retrieved from the Earth System Grid Federation (ESGF) data portal.

3. Methodology

3.1 Selection of validation areas and ground stations

The evaluation of multiple daily, dekadal (10 days), and monthly rainfall, T-max, and T-min products were conducted on selected basins of Ethiopia (EthioShed1 - EthioShed17), Kenya (KenShed1 and KenShed2), and Tanzania (TanzShed1 and TanzShed2) (Fig. 1). The polygons in Fig. 1 are river basins retrieved from the global river basins available at the WaterBase hosted by the United Nations

University (UNU-INWEH: http://www.waterbase.org/). In most regions of Africa not only are the density and availability of field-based meteorological stations limited, but their accessibility is very restricted for many reasons. For this study, it was only possible to get daily station data from the National Meteorological Agency (NMA) of Ethiopia with a reasonable spatial and temporal coverage. Therefore, the selection of validation areas is based on the availability, quality, and density of field-based meteorological stations during the period of 1983–2005. It was almost impossible to find multiple stations in one satellite grid cell. For Kenya and Tanzania, therefore, stations with more than 10 years (>50 % of the study period), were included for evaluation (Table 1).

The quality of selected stations was checked and extremely high rainfall records during dry seasons, such as daily rainfall of > 480 mm preceding and following by dry days, were excluded. Finally, a total of 132 stations were found suitable for comparison, 2 to 12 stations located in the validation areas. In addition to these stations in the validation areas, 78 stations, randomly distributed over the region, are used to compare on individual basis with the rainfall and temperature products. Compared to Kenya and Tanzania, the quality, continuity, and spatial and temporal coverage of stations were better in Ethiopia and only stations with missing values of less than 20 % were considered. The availability of multiple stations in a validation area helps to check the quality of individual stations by using methods such as double mass curve (Vernimmen et al., 2012) and allows for replacement of missing values of one station from a nearby station.

3.2 Comparing ground data with satellite, observational reanalysis, and climate model-based data

The most commonly used method to compare ground observations with other data products such as satellite based rainfall estimates and climate model outputs is point (station) to pixel comparison. When comparing daily rainfall, particularly in very complex topography, on point to pixel basis it can be challenging to acquire reasonable agreements. Therefore, in this study we used point to pixel, point to area grid cell average, and stations average to area grid cell average to evaluate the accuracy of each product. Area grid cell average is the average of numbers of pixels covering the basin or the validation area. Similarly, station average is used to indicate the average value of the stations inside the validation area. Therefore, during the comparison process, individual or the stations average is compared to the area grid cell average of the product. The most commonly used statistical methods such as the Pearson correlation coefficient (CC), bias, relative bias (Rbias), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Index of Agreement (IA) (Cohen Liechti et al., 2012; Daren Harmel and Smith, 2007; Moazami et al., 2013) are used. CC (Eq. 1) is applied to evaluate the agreement of individual products (P) to station data (O). A value of CC close to one shows a perfect positive fit between the products and station data.

$$\mathrm{CC} = \frac{\sum_{i=1}^{N}(P_i - \bar{P}) \cdot (O_i - \bar{O})}{\sqrt{\sum_{i=1}^{N}(P_i - \bar{P})^2} \cdot \sqrt{\sum_{i=1}^{N}(O_i - \bar{O})^2}} \tag{1}$$

The average differences and systematic bias of each product are given as bias (Eq. 2) and Rbias (Eq. 3). Bias can be positive (overestimation) or negative (underestimation) according to the accuracy of each product.

$$\mathrm{Bias} = \frac{\sum(P_i - O_i)}{N} \tag{2}$$

$$\mathrm{Rbias} = \frac{\sum_{i=1}^{N}(P_i - O_i)}{\sum_{i=1}^{N} O_i} \times 100 \tag{3}$$

The MAE and RMSE (Eq. 4 and 5), are well-known and accepted indicators of goodness of fit that shows the differences between ground observation and model or other product outputs (Legates and McCabe, 1999).

$$MAE = \frac{\sum_{i=1}^{N}|O_i - P_i|}{N} \tag{4}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(\mathrm{O_i} - \mathrm{P_i})^2}{\mathrm{N}}} \tag{5}$$

The IA (Willmott, 1981) is another widely used indicator of goodness of fit between observed and model output. IA (Eq. 6) describes how much of the model or product output (rainfall, T-max, and T-min products) are error-free compared to the ground observations.

$$\mathrm{IA} = \frac{\sum (P_i - O_i)^2}{\sum (|\mathrm{P} - \bar{\mathrm{O}}| + |\mathrm{O} - \bar{\mathrm{O}}|)} \tag{6}$$

In addition to the above statistical methods, the Taylor diagram (Taylor, 2001) is used to summarize the statistical relationship between ground station data and the products for rainfall, T-max, and T-min. In this diagram, the relationships between the two fields are explained by correlation coefficient (R), the centered mean square (RMS) difference (E´), and standard deviation (σ). The diagram is useful for evaluating the accuracy of multiple data sources or model output against a reference or observational data (IPCC, 2001). A single point on the diagram displays three statistical values (R, E´, and σ) and their relation is given by Eq. (7).

$$E'^2 = \sigma_f{}^2 + \sigma_r{}^2 - 2\sigma_f \sigma_r R \tag{7}$$

Where σ_f^2 and σ_r^2 are the variance of the model and observation fields and R is the correlation coefficient between the two fields (Eq. 8).

$$R = \frac{\frac{1}{N}\sum_{n=1}^{N}(f_n - \bar{f})(r_n - \bar{r})}{\sigma_f \sigma_r} \tag{8}$$

In the diagram, the distance from the reference point (observed data) is given as the centered RMS difference of the two fields (Eq. 9). A model with no error would show a perfect correlation to the observation.

$$E'^2 = \frac{1}{N}\sum_{n=1}^{N}[(f_n - \bar{f}) - (r_n - \bar{r})]^2 \tag{9}$$

Where *f* is the test (e.g. model or satellite) field and *r* is reference (observed) field, whereas $\sigma_f \sigma_r$ are the standard deviations of the model and reference fields (Eqs. 10 a and b).

$$\sigma_f = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(f_n - \bar{f})^2} \tag{10a}$$

$$\sigma_r = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(r_n - \bar{r})^2} \tag{10b}$$

Additionally, rainfall characteristics such as the number wet days, duration and amount of wet periods, duration of dry periods, and daily and total rainfall are used to evaluate the accuracy of individual rainfall products by comparing to the observed data. Rainfall characteristics are widely used indicators in rainfall modelling (Wilby and Dawson, 2007; Jebari et al., 2012) and include: Number of wet days (days y^{-1}), which is the count of days with rainfall per year; duration (days) of wet and dry periods indicating the average number of consecutive wet and dry days during the study period; the amount of wet periods (mm), indicating the amount of rainfall observed during the identified wet period.

4. Results

4.1 Validation of satellite, observational reanalysis, and climate model-based products

The average daily rainfall (Fig. 2) of the study region retrieved from ARC2, CHIRP, CHIRPS, ORH, individual RCMs (RCM) and RCMs mean (RCMs) displays large discrepancies between the products for the study period 1983–2005. Compared to dekadal and monthly resolution, the comparison at daily time scale, particularly of rainfall, is challenging and more emphasis is given on this evaluation. RCMs (RCA4 and CCLM) driven by HadGEM2-ES (HadGEM2), MPI-ESM-LR (MPI), and GFDL-ESM2M (GFDL) are used in this study. For RCMs driven by each GCM, the average is used. The daily rainfall, T-max, and T-min maps of GFDL display the result of single RCM (RCA4) driven by GFDL-ESM2M for the period of 1983-2005. Higher and lower average daily rainfall values are displayed by GFDL and ORH, respectively (Fig. 2). However, all the products showed a similar tendency in capturing the daily rainfall distribution; higher in west and lower in the east part of the region. In addition, the average daily T-max and T-min (Fig. 3) of the region shows relatively higher disagreement between ORH and individual RCMs (RCM). However, RCM shows a higher agreement in Ethiopia, Kenya, and Tanzania for T-max and T-min.

The relation of each product with station data is given by scatter plots in Fig. 4 for eight validation areas, four in Ethiopia, two in Kenya, and two in Tanzania. The same plots – with similar results - for another 13 areas in Ethiopia are provided in the supplementary material (SF. 1). The monthly rainfall plots display the relationship of each product with observed ground data and this relation is explained by the coefficient of determination or R-Squared (R^2). Based on the scatter plots, CHIRPS and CHIRP are the most accurate rainfall products, with higher correlation and lower RMSE, and ARC2 and ORH are the second best products. RCM and RCM's mean (RCMs) correlate weakly in most of the validation areas. In addition, RCM (not shown in Fig. 4) and RCMs show a strong over- and underestimation of monthly rainfall compared to the other products. In EthioShed1, for example, CHIRPS and CHIRP are shown to be the most accurate products, while ARC2 and ORH showed higher dispersion above and below the regression line. Similarly, in EthioShed4 both CHIRP and CHIRPS have an equal R^2, but in terms of biases (points below and above the regression line) CHIRPs performed better. The observed biases in CHIRP and higher correlations in CHIRPS in all the valiation areas highlights the role of the station-satellite data blending techniques. Compared to other validation areas, the agreement of products in EthioShed16 is comparably weak and CHIRPS and CHIRP showed the higher R^2 (0.48) compared to ARC2, ORH, and RCMs.

As for the daily, dekadal, and monthly resolution, the comparison is performed in three ways: point to pixel, point to area grid cell average, and stations average to area grid cell average using the methods described in Section 3.2. An explanatory example is given in Table 2, using stations of EthioShde1 displaying the difference in comparing products through point (station) to pixel, point to area grid cell average, and stations average to area grid cell average. The agreement of each product with station data on a daily time scale and on point to pixel comparison is weak, with significantly higher biases and errors. For rainfall, in general, the latter method, stations average to area grid cells average, provides better correlation, higher index of agreement, and lower biases and errors. Compared to point to pixel, the stations average to area grid cells average improves the correlations of ARC2, CHIRP, and CHIRPS by 81.3 %, 65.7 %, and 8 %, respectively. In addition to the correlation, the method reduces the RMSE by more than 66 %. Compared to ARC2 and CHIRP (Table 2), CHIRPS gives a significantly higher correlation and IA and lower biases and RMSE. During area averaging, extremely high rainfall events obtained for a location from the various data products are levelled off by averaging and this makes the product more representative for the area. In most of the rainfall products there are occasionally higher daily rainfall values recorded and the averaging removes those extremes, which are much higher than the observed station data in the area. Compared to point to pixel, the second method, point to area grid cell average, provides a reasonable correlation.

The agreement of each product increases with decreasing temporal resolution, from daily to dekadal and monthly resolutions. Including the historical data of each RCM, RCMs, and ORH, the overall comparison using some of the statistical methods is summarized in Tables 3, ~~4~~5, and ~~5~~ 6 for rainfall, T-max, and T-min, respectively. The evaluation of each rainfall product (ARC2, CHIRP, CHIRPS, ORH, and RCMs) showed a different degree of agreement with station data (Table 3). The same table for individual RCMs (RCM) for all the validation areas is provided in the supplementary material (ST 1). At daily time scale, CHIRPS followed by ARC2 and CHIRP proved to be the most accurate rainfall products compared to ORH, RCM, and RCMs in all the validation areas. In general, out of the 21 validation areas CHIRPS, ARC2, and CHIRP showed a higher correlation in 17, three, and one validation areas, respectively. In addition to the higher correlation, CHIRPS, CHIRP, and ARC showed lower RMSE than ORH, RCM, and RCMS. Similarly, CHIRPS and CHIRP showed lower biases than observed in ARC2, ORH, RCM, and RCMs in most of the validation areas.

On average, over the 21 validation areas, CHIRPS captures well the number of wet days (~~99.8~~-0.17 % deviation), average duration of wet (~~87.5~~-13.4 % deviation) and dry periods (~~84~~ -17.6 % deviation), total rainfall (~~95.6~~-4.5 % deviation), average amount of wet periods (~~84.3~~-17 % deviation), and average daily rainfall ~~intensity~~ (~~93~~ -7.7 % deviation) (Table 4). Next to CHIRPS, ARC2 showed higher agreement in producing average duration of wet (~~82~~ -20 % deviation) and dry periods (~~112~~ +11.3 % deviation) and average amount of wet periods (~~68~~ -38 % deviation). CHIRP on the other hand showed a higher agreement in the total amount of rainfall with a 2.75 % deviation~~by 103 %~~, which is higher than

CHIRPS, ARC2, ORH, RCM, and RCMS. On the contrary, ARC2 and GFDL showed higher under- (-~~30~~ 34.7 % deviation) and overestimation (~~31~~ 27.2 % deviation), respectively, of the total amount of rainfall compared to the other products. In addition, ARC2 showed a higher underestimation in number of wet days (-~~14~~ 15.1 % deviation) and average daily rainfall ~~intensity~~ (-~~21~~ 23.8 % deviation) compared to CHIRPS and ORH. CHIRP on the other hand, showed higher overestimation in number of wet days~~,~~ and duration~~,~~ and amount of wet ~~days~~ periods (> ~~85~~ 59.7 % deviation) and underestimates duration of dry periods and average daily ~~intensity~~ rainfall (-~~47~~ 62 % deviation) compared to the other products. Moreover, RCMs, next to CHIRP, showed higher overestimation in number of wet days~~,~~ and duration and amount of wet ~~days~~ periods (> ~~58~~ 44.9 % deviation) and total rainfall amount (~~12~~ 11.4 % deviation) and underestimate average duration of dry ~~days~~ periods and daily rainfall ~~intensity~~ by about ~~34~~ 41 %. In general, the observed rainfall characteristics are well captured by CHIRPS, with a percentage difference from the observation of -0.17 % to -17.6 % –for number of wet days and duration of dry periods, respectively, compared to CHIRP, ARC2, ORH, RCM, and RCMs (Table 4).

For T-max and T-min, only ORH, RCM, and RCMs are compared with station data. For 21 validation areas ORH data proved to be the most accurate product for both T-max (Table ~~4~~5) and T-min (Table ~~5~~6). In comparison to RCM and RCMs, ORH showed a significantly higher correlation and lower biases and errors in most of the validation areas. In seven of the 21 validation areas, RCMs showed a higher correlation in T-max than ORH and RCM. However, for T-min, ORH in 20 of the 21 validation areas showed a higher correlation. In general, RCM and RCMs showed higher RMSE and biases in most of the validation areas compared to ORH. Next to ORH and compared to RCM, RCMs appeared to be the best data source particularly for T-max. RCMs showed a relatively higher correlation and lower biases and errors compared to RCM in most of the validation areas.

4.2 Validation of satellite, observational reanalysis, and climate model-based products at dekadal and monthly resolutions

To understand the role of higher spatial resolution at improving the agreement with station data, a similar statistical evaluation was performed using the coarse resolution of CHIRPS (0.25°). Compared to the coarse resolution of CHIRPS, the daily improved version (0.05º) used in this study showed an increased correlation of up to 3.2 % in all the validation areas. In line with the daily evaluation, the comparison was extended to dekadal and monthly resolutions for rainfall, T-max, and T-min using the same statistical methods. For this analysis the observed daily ground observations and data from ARC2, CHIRP, CHIRPS, ORH, RCM, and RCMs were aggregated to dekadal and monthly resolutions. With decreasing temporal resolution (daily to monthly), the agreement of each product showed a marked improvement in all the validation areas. In addition to the increase in correlation, biases (bias and Rbias) and errors (MAE and RMSE) in rainfall are decreased at dekadal and monthly resolutions.

At dekadal and monthly resolution, the agreement of all rainfall products with station data increased compared to daily resolutions and the result for eight validation areas of Ethiopia, Kenya, and Tanzania are given in Fig. 5. The same plots – with similar results - for another 13 areas are provided in the supplementary material (SF. 2). Similar to the daily evaluation, CHIRPS appeared to be the most accurate rainfall product both at dekadal and monthly resolutions in most of the validation areas compared to the other products. In addition to the higher correlation of CHIRPS with station data at monthly and dekadal time scale, the centered mean square (RMS) difference and standard deviation is close to the observation in most of the validation areas. Following CHIRPS, CHIRP appeared to be the second best data source for dekadal and monthly rainfall and in three validation areas (EthioShed3, 15, and 16) showed a slightly higher correlation than CHIRPS. In two validation areas (KenShed1 and 2), ARC2 showed a slightly higher correlation than CHRIP and CHIRPS. However, in KenShed2 ARC2 showed a higher deviation from the observed value compared to CHIRP and CHIRPS. CHIRPS has, for example, almost similar standard deviation as the station data in all the validation areas except in areas with lower number of ground stations (EthioShed12–15 and TanzShed1). Overall, CHIRPS, CHIRP, and ARC2 were found to be the best performing rainfall product while ORH, RCM, and RCMs are the least performing products.

Moreover, for T-max and T-min, the correlation of ORH, RCM, and RCMs increased from daily to dekadal and monthly resolutions. The agreement of each product with station data, for eight validation areas of Ethiopia, Kenya, and Tanzania, is given in Fig. 6 and Fig. 7 for T-max and T-min, respectively.

The same plots – with similar results - for another 13 areas are provided in the supplementary material (SF. 3 and SF. 4 for T-max and T-min, respectively). Compared to RCM and RCMs, the correlation between ORH and station data is higher in most of the validation areas. In addition, ORH showed lower centered mean square (RMS) difference and biases (bias and Rbais). In addition, compared to the RCM and RCMs the standard deviation of ORH is close to the respective observations in most of the validation areas. Compared to RCM, the standard deviation and centered mean square (RMS) difference of RCMs is lower in most of the validation areas.

5. Discussion

Detection of rainfall characteristics by satellite observations or climate model simulations' output (GCM and RCM) is very challenging as compared to temperature. This is especially evident in East Africa, where the topography is complex and characterized by multiple rainfall regimes. In particular, it is difficult to estimate rainfall with satellite imageries in the mountainous region of East Africa (Cattani et al., 2016) because these products are inevitably not representing the regional rainfall patterns and complexity of the region's topography (Romilly and Gebremichael, 2010). Here, for an improved understanding of the climatic condition of this complex region and its impact on environmental resources, daily rainfall, T-max, and T-min products from high resolution satellite imageries, observational-reanalysis, and climate models outputs are compared against ground observations. Such an evaluation was not available as of yet for the considered region. Therefore, an in-depth evaluation was performed, particularly on a daily time scale, of the satellite-based rainfall products (ARC2 CHIRPS and CHIRP), ORH, and RCMs (CCLM and RCA) driven by three GCMs. ARC2, CHIRP, and CHIRPS are rainfall products, whereas ORH and RCMs provide rainfall, T-max, and T-min.

From the comparison (using point to pixel, point to area grid cell average, and stations average to area grid cell average), the stations average to area grid cell average showed the best correlation and least biases and errors in all the validation areas. A study by Duan et al., (2016) in Adige Basin (Italy) found that comparing rainfall products such as CHIRPS on a watershed scale showed a marked improvement in overall agreement compared to point to pixel on daily and monthly time scale. Comparing the coarse resolution of satellite products and of RCMs using the point to pixel method cannot be expected to result in a high agreement with station data. Ground stations provide point data measured over continuous time periods, whereas satellite products provide area averages based on discontinuous (rain) estimates. Field-based stations (as point measurements) cannot be considered as reference data for evaluation of area-based rainfall estimates (Cohen Liechti et al., 2012; Wang and Wolff, 2010), if not compared at a monthly or annual time scale. This is similar to our finding that the point to pixel comparison for all products inside and outside the validation areas show weak statistical relations with ground stations (e.g. see Table 2). The correspondence of all products at a daily time scale and in all the validation areas was found comparably weak and the findings are in agreement with earlier studies (Cohen Liechti et al., 2012; Dembélé and Zwart, 2016).

At daily time scale, CHIRPS followed by ARC2 and CHIRP showed higher correlation and lower errors and biases in all the validation areas compared to ORH, RCM, and RCMs. In addition, CHIRPS captures the daily rainfall characteristics well while ARC2 showed higher underestimation of the average daily and total rainfall~~ and intensity~~. The agreement of all the rainfall products increases from daily to dekadal and monthly time scale (Fig. 5) and this is consistent with other studies (Cohen Liechti et al., 2012; Dembélé and Zwart, 2016; Kimani et al., 2017).

Generally, CHIRPS with high spatial resolution, followed by CHIRP and ARC2, was the best performing rainfall product in terms of correlation, biases and errors and in characterizing regional rainfall characteristics. By contrast, ORH, RCM, and RCMs appeared to be less precise rainfall products at all time scales and in all validation areas. When looking at the performance of different data products in the selected validation areas (Fig. 4), dispersion is comparably higher in areas with lower number of ground stations. An additional confounding factor could be the very complex topography of the region. This might explain why products with coarser spatial resolution (ORH, RCM, and RCMs) showed higher dispersion compared to products with higher spatial resolution (CHIRPS, CHIRP, and ARC2).

The daily rainfall data (global summary of the day) available at the National Climate Data Center (NCDC) needed to be controlled for quality before application. In East Africa, particularly Ethiopia, the available data at NCDC is very poor and only few stations are available. Therefore, products developed based on the global summary of the day such as ORH cannot be expected to provide accurate results particularly for the most complex climate variable, rainfall, as CHIRPS and ARC2. CHIRPS incorporates monthly station data obtained from different regional meteorological organization, e.g., from Ethiopia, Kenya, and Tanzania. In all the validation areas one to seven stations were included in the development of CHIRPS in different months during 1981–2005. In EthioSded1 (Table 2), for example, six of the nine stations we considered in this study are included in CHIRPS. The inclusion of monthly station data can be assumed to improve CHIRPS´ performance compared to other rainfall products. This particular feature of CHIRPS (compared to CHIRP and other data products) is somewhat problematic for our analysis, since the correlated data are not fully independent. However, since only monthly data from a limited number of stations were included in CHIRPS, the dependency is rather weak and indirect. In fact, the improved performance of CHIRPS was shown even in areas were station data is not included (e.g. Arijo, Bedele, and Hurma stations in EthioShed1) and on daily time scale.

Even though ORH was one of the least performing rainfall product, it appeared to be the most accurate data source for T-max and T-min at daily, dekadal, and monthly resolutions compared to RCM and RCMs. Nikulin et al., (2012) presented a detailed comparison of daily gridded observations with multiple RCMs including RCA and CCLM and they found large discrepancies over the whole region of Africa. However, in this region, RCMs appeared to be the second best data source for both T-max and T-min and RCM are less precise with slightly higher biases and errors. In this region, other studies (Endris et al., 2013; Kim et al., 2014) concluded that the multi-model or ensemble mean of CORDEX RCMs provides reasonable results compared to individual RCMs (RCM). The systematic bias of RCM and RCMs is higher in most of the validation areas compared to the other products, particularly for rainfall, that can be improved by applying different bias correction techniques such as the empirical quantile mapping (Lafon et al., 2013; Maraun, 2013; Teng et al., 2015) before application to different hydrological and climate models.

6. Summary and Conclusion

The evaluation of rainfall, T-max, and T-min from different sources against station data was performed for large parts of East Africa (Ethiopia, Kenya, and Tanzania) using three methods: point to pixel, point to area grid cell average, and stations average to area grid cell averages. Compared to the other two methods the latter method (stations average to area grid cell average) provides a better correlation and index of agreement (IA) and lower errors (MEA and RMSE) and biases (bias and Rbias). Using this method, individual rainfall, T-max, and T-min products were compared at daily, dekadal (10 days), and monthly resolutions. At daily time CHIRPS, ARC2, and CHIRP provide a better agreement with station data compared to ORH, RCM, and RCMs. Compared to CHIRPS and CHIRP, ARC2, ORH, RCM, and RCMs showed higher biases and errors in most of the validation areas. Overall, the performance of CHIRPS is higher than the other rainfall products in capturing the daily rainfall characteristics such as number of wet days, ~~and~~ duration of wet and dry ~~days~~periods, total ~~rainfall,~~and daily ~~intensity~~rainfall, and amount of wet periods. ARC2 better captures duration of wet and dry periods, but showed higher underestimation of the total ~~rainfall,~~ and daily ~~intensity~~ rainfall and number of wet days compared CHIRPS and CHIRP. RCM and RCMs, on the other hand, showed higher overestimation in number of wet days, duration~~,~~ and amount of wet ~~days~~ periods, and total rainfall and underestimate average duration of dry ~~days~~ periods and daily rainfall ~~intensity~~.

ORH, on the contrary, appeared to be one of the least-performing rainfall products for the study region, but the most accurate product, compared to RCM and RCMs, for T-max and T-min at daily time scale in most of the validation areas. The evaluation of the above products at dekadal and monthly time scales showed that CHIRPS with high spatial resolution (0.05°) has higher correlation and lower errors and biases than the other rainfall products. As the temporal resolution gets coarser (e.g. monthly), the correlation between ground observation and the above products significantly increases. In addition, biases (bias and Rbias) and errors (MAE and RMSE) significantly decreased. Similar to that of rainfall, the comparison at dekadal and monthly resolution showed an improved correlation and lower errors and biases for both T-max and T-min. Compared to RCM and RCMs, ORH with higher spatial resolution was found to be more accurate at dekadal and monthly resolutions. Next to ORH, RCMs showed a better performance than RCM, with lower biases and errors.

In general, CHIRPS for rainfall and ORH for T-max and T-min performed best in the considered regions of Ethiopia, Kenya, and Tanzania. Further studies need to confirm whether this finding holds for other regions as well and our approach may represent a blueprint how to address this question. Since CHIRPS and ORH are available with higher spatial and temporal resolution and for longer periods, these data sources can be used for long-term climate studies (trend, variability, and extreme indices) and input for climate or hydrological models. Considering the typical need for daily data for model input, it remains to be investigated whether poor daily data with a limited bias and similar variance are an acceptable replacement of missing station data when used for impact model studies. In addition, the products can be used to check the plausibility of available ground stations, or substitute ground observation in ~~areas~~ regions of Ethiopia, Kenya, and Tanzania where ground station~~s~~ data are not available or accessible.

Table 1: General characteristics of selected validation areas and meteorological stations covering the time period 1983–2005.

Validation areas/basins	Basin area (km^2)	Average area elevation (m)	Number of stations	Average station elevation (m)	Average annual rainfall (mm)	Average T-max /T-min
EthioShed1	8980	1516	9	1881	1758	26.3/13.6
EthioShed2	12828	2279	12	2009	968.6	25.9/11.4
EthioShed3	15123	2192	9	2104	1202.6	25.3/11.7
EthioShed4	8323	2180	7	1954	994.42	31.8/16.5
EthioShed5	5625	1720	10	1800	1039.1	26.4/13.4
EthioShed6	11204	2830	8	2510	1168.7	22.1/8.0
EthioShed7	12445	1830	8	1973	1524.53	25.7/12.4
EthioShed8	6522	1930	5	2022	1628.35	26.0/14.0
EthioShed9	4666	1526	4	1738	578.4	28.0/14.4
EthioShed10	5986	2520	8	2580	1133.1	21.2/9.3
EthioShed11	11496	1256	7	1468	945	27.4/15.2
EthioShed12	3868	520	2	400	343.8	34.1/22.3
EthioShed13	4934	1301	4	2413	588	26.2/13.1
EthioShed14	2835	1360	4	1239	706	31.8/16.5
EthioShed15	1121	2307	4	2183	495	24.3/11.1
EthioShed16	3012	2102	5	2148	1110	26.0/11.8
EthioShed17	9909	1998	12	2056	2075	23.8/10.2
KenShed1	11712	1980	4	1024	1156.1	25/13.5
KenShed2	7861	2328	3	1602	1418.6	24/13.2
TanzShed1	8092	1244	3	1137	1137.8	28.7/17.5
TanzShed2	2154	1097	3	1428	1136.2	28.2/17.8

Table 2: An example of the statistics used to compare ground rainfall data with satellite products (e.g. ARC2, CHIRP, and CHIRPS) in EthioShed1. The three modes of comparison are compared based on a range of statistical variables (section 3.2). The Point (station) to area grid cell average is computed by comparing individual station to the area grid cell average of each product. Best fit of the last three rows is indicated in bold, best fit of the nine stations are also highlighted.

Station	ARC2						CHIRP						CHIRPS					
	CC	Bias	Rbias	MAE	RMSE	IA	CC	Bias	Rbias	MAE	RMSE	IA	CC	Bias	Rbias	MAE	RMSE	IA
Anger	0.32	-0.55	-14.7	4.64	10.48	0.52	0.37	0.45	11.9	4.87	9.58	0.56	0.40	-0.15	-4.1	4.40	9.40	0.6
Arijo	0.29	-1.25	-37.6	5.02	10.14	0.53	0.23	0.12	3.4	5.94	10.29	0.49	0.37	-0.42	-12.5	5.08	9.33	0.61
Bedele	0.33	-1.40	-28.7	5.00	10.67	0.55	0.34	-0.45	-9.3	5.21	9.32	0.55	0.41	-0.54	-11.1	4.96	9.30	0.62
Dedesa	0.29	-0.71	-18.0	4.77	10.53	0.51	0.28	0.13	3.4	5.16	10.49	0.50	0.34	-0.23	-5.8	4.81	9.92	0.55
Gimbi	0.32	-1.03	-23.9	5.10	10.78	0.55	0.39	0.12	2.8	5.17	9.85	0.59	0.42	-0.20	-4.5	4.91	9.76	0.64
Nekemt	0.44	-1.20	-23.4	4.71	10.69	0.64	0.38	0.02	0.3	5.79	10.96	0.59	0.41	-0.75	-14.6	5.30	10.44	0.62
Alge	0.32	-1.08	-27.6	5.13	10.2	0.55	0.36	-0.45	-11.7	4.99	9.12	0.56	0.37	-0.36	-9.4	5.36	10.01	0.6
Ayira	0.3	-1.02	-26.1	5.18	10.68	0.53	0.40	-0.18	-4.80	4.95	8.98	0.60	0.36	-0.37	-9.6	5.41	10.07	0.6
Hurma	0.31	-1.01	-25.7	5.20	10.44	0.54	0.38	-0.56	-14.5	4.59	8.86	0.54	0.37	-0.60	-15.8	5.15	9.59	0.6
Average of point – pixel	0.32	-1.03	-25.1	**4.97**	10.51	0.55	0.35	-0.09	**-2.06**	5.19	**9.72**	0.55	**0.38**	**-0.40**	-9.7	5.04	9.76	**0.6**
Average of point – area grid cells average	0.37	-1.1	-26.8	**4.82**	9.59	0.53	0.37	-0.21	**-5.5**	10.18	9.51	0.54	**0.40**	**-0.46**	-11.5	4.86	**9.38**	**0.58**
Stations average - area grid cells average	0.58	-1.3	-27.3	5.66	3.22	0.74	0.58	-0.27	**-5.7**	5.6	3.29	0.75	**0.64**	**-0.59**	-12.0	**5.38**	**3.08**	**0.79**

Table 3: Evaluation results of multiple daily rainfall products against field meteorological stations covering the period of 1983–2005 for 21 validation areas of East Africa. For ease of comparison, only selected statistical estimators are given in the table. For individual RCMs) their mean (RCMs) is given here. Best fit is indicated in bold.

Validation area	ARC2			CHIRPS			CHIRP			ORH			RCMs		
	CC	Rbias	RMSE	CC	Rbias	RMSE	CC	Rbias	RMSE	CC	Rbias	RMSE	CC	Rbias	RMSE
EthioShed1	0.59	-31.2	5.64	**0.64**	**-5.7**	**5.5**	0.57	-7.2	5.7	0.20	-16.7	10.81	0.52	-37.2	6.1
EthioShed2	0.58	-27.3	5.66	**0.64**	-12.0	**5.38**	0.58	**-5.7**	5.6	0.18	19.8	8.6	0.43	45.8	4.8
EthioShed3	0.63	-29.4	4.68	**0.69**	-12.6	**4.37**	0.64	-10.8	4.46	0.25	-11.7	9.86	0.60	**-4.8**	4.65
EthioShed4	0.59	-37.4	**4.95**	**0.61**	**1.9**	5.34	0.49	3.9	5.35	0.12	-1.5	12.14	0.30	38.7	6.38
EthioShed5	0.40	-11.8	4.65	**0.43**	12.1	4.72	0.39	**8.7**	**4.35**	0.10	24.5	8.48	0.14	-9.3	4.68
EthioShed6	0.47	-42.6	**3.55**	**0.64**	**5.20**	3.66	0.47	5.6	3.65	0.11	16.8	7.73	0.21	60.5	6.74
EthioShed7	0.55	-27.8	5.27	**0.70**	**-1.4**	**4.68**	0.49	4.9	5.64	0.12	-13.6	10.7	0.38	-3.9	5.77
EthioShed8	0.33	-22.7	7.29	**0.46**	-2.7	6.56	0.44	**-2.0**	**5.60**	0.11	-22.4	12.0	0.37	21.8	7.28
EthioShed9	0.30	**-7.2**	5.16	**0.33**	-9.4	4.43	0.28	-26.0	**4.03**	0.06	-22.1	7.46	0.07	-39.4	4.38
EthioShed10	0.59	-38.2	**4.36**	**0.60**	**-0.7**	4.81	0.53	-2.7	4.70	0.18	14.8	10.92	0.45	39.4	5.21
EthioShed11	0.45	-38.1	4.58	**0.48**	**0.2**	4.86	0.43	-0.9	**4.37**	0.10	-10.9	7.33	0.13	-51.9	4.73
EthioShed12	**0.42**	-31.3	**3.75**	0.35	31.5	4.15	0.32	24.3	4.0	0.1	35.1	5.58	0.07	**-14.8**	4.10
EthioShed13	0.46	-38.0	5.50	**0.52**	-14.4	**5.2**	0.37	-15.4	5.70	0.13	-13.2	9.35	0.26	**12.4**	5.92
EthioShed14	0.40	-14.3	4.76	**0.41**	**2.0**	4.78	0.35	-2.0	**4.53**	0.10	13.7	7.85	0.12	-48.7	4.75
EthioShed15	0.39	-35.3	4.72	**0.45**	**-11.3**	**4.58**	0.35	-15.5	4.74	0.11	97.2	8.4	0.18	37.9	5.11
EthioShed16	0.29	-42.3	5.06	**0.35**	12.2	5.72	0.29	**3.9**	**5.04**	0.12	12.7	7.89	0.16	11.2	5.17
EthioShed17	0.45	-25.4	3.89	0.56	**7.0**	3.82	0.46	9.3	**3.75**	0.13	23.8	7.67	0.20	-14.4	4.1
KenShed1	**0.62**	**6.4**	**3.5**	0.4	58.6	5.56	0.31	45	5.60	0.36	21	5.65	0.1	22.1	4.72
KenShed2	**0.72**	-22	**4.39**	0.38	**-4.9**	8.72	0.38	24.2	6.88	0.5	22.1	7.23	0.2	67.3	7.56
TanzShed1	0.3	-40	5.83	**0.43**	-29	**5.7**	0.40	30.7	6.03	0.24	**13.7**	7.44	0.13	38.2	6.4
TanzShed2	0.3	**7.2**	0.23	**0.44**	19	**0.2**	0.38	36.2	5.5	0.11	12	0.3	0.21	22	0.21

Table 4: Summary of daily rainfall characteristics retrieved from multiple rainfall products and averaged over the validation areas of Ethiopia, Kenya and Tanzania. Values in brackets give the deviation from the observed value (%). The value which comes closest to the observed value is highlighted in bold.

Rainfall characteristics	Obs.	ARC2	CHIRP	CHIRPS	ORH	HadGEM2	MPI	GFDL	RCMs
Number of wet days (days/year)	189.58	162.98 (-15.1)	351.06 (59.7)	**189.26** (-0.17)	192.14 (1.34)	205.08 (7.85)	243.55 (24.92)	210.42 (10.42)	299.36 (44.9)
Average duration of wet periods (days)	5.86	4.78 (-20)	167.96 (186)	**5.13** (-13.4)	3.02 (-64)	11.70 (66.5)	12.17 (69.9)	9.37 (46)	21.36 (113.9)
Total amount of precipitation (mm/year)	953.63	671.62 (-34.7)	**980.24** (2.75)	912.0 (-4.5)	1027.02 (7.41)	841.73 (-12.5)	1055.7 (10.2)	1253.38 (27.2)	1068.6 (11.4)
Average amount of wet periods (mm)	30.20	20.56 (-38)	498.43 (177)	**25.46** (-17)	15.64 (-63.5)	50.12 (49.6)	55.45 (59)	59.64 (65.6)	78.88 (89.3)
Average duration of dry periods (days)	5.37	6.01 (11.3)	1.53 (-111.3)	4.5 (-17.6)	2.55 (-71.31)	6.91 (25.04)	**5.67** (5.4)	6.55 (19.8)	3.55 (-41)
Average daily precipitation (mm/day)	5.28	4.16 (-23.8)	2.78 (-62)	4.88 (-7.7)	**5.4** (2.3)	3.88 (-31.5)	4.19 (-22.8)	5.69 (7.6)	3.48 (-41)

Table ~~4~~5: Statistical evaluation of daily T-max retrieved from climate model and reanalysis-based products against ground observations over the period of 1983–2005 for 21 validation areas of East Africa. For ease of comparison, only selected statistical estimators are given in the table. Best fit is indicated in bold.

Validation areas	ORH			HadGEM2~~Had~~			GFDL			MPI			RCMs		
	CC	Rbias	RMSE	CC	Rbias	RMSE	CC	Rbias	RMSE	CC	Rbias	RMSE	CC	Rbias	RMSE
EthioShed1	0.63	**3.1**	2.65	0.71	-3.5	2.83	0.56	-3.2	3.04	0.68	-6.2	-6.2	**0.72**	-4.3	**2.56**
EthioShed2	**0.63**	**-7.9**	**2.77**	0.57	-17.0	5.07	0.48	-21	5.95	0.51	-19.3	5.57	0.63	-19.1	5.30
EthioShed3	0.71	**4.1**	**2.30**	0.77	-6.7	2.72	0.39	-6.8	3.24	0.73	-8.9	3.09	**0.78**	-7.5	2.53
EthioShed4	**0.64**	**5.0**	**2.67**	0.42	-15.6	4.95	0.52	-19.1	5.74	0.43	-16.9	5.22	0.56	-17.2	5.06
EthioShed5	0.61	**2.1**	**2.25**	0.63	**-5.6**	3.12	0.46	-10.3	3.98	0.62	10.1	3.83	**0.65**	-8.7	3.23
EthioShed6	**0.70**	**-3.3**	**1.69**	0.53	-11.6	3.51	0.45	-19.4	4.87	0.48	-15.6	4.16	0.58	-15.6	3.92
EthioShed7	0.63	**-2.8**	**2.30**	0.63	-13.8	4.48	0.52	-14.5	4.77	0.64	-16.7	4.99	**0.66**	-15.0	4.51
EthioShed8	0.63	**1.4**	**2.33**	0.65	**-7.7**	3.31	0.56	-10.8	4.10	0.65	-12.4	4.11	**0.69**	-10.3	3.50
EthioShed9	**0.35**	**2.3**	**2.59**	0.30	-7.4	3.51	0.28	-12.8	4.89	0.21	-9.5	4.1	0.33	-9.9	3.81
EthioShed10	**0.51**	17.8	4.40	0.45	**-0.5**	2.70	0.34	-4.1	2.90	0.39	-2.9	2.72	0.50	-2.5	**2.27**
EthioShed11	0.52	1.6	2.4	0.54	3.0	2.78	0.45	-0.9	3.1	0.56	-1.6	2.84	**0.60**	**0.2**	**2.34**
EthioShed12	0.42	**-1.2**	**2.23**	0.43	-5.3	2.96	0.16	-6	3.6	0.44	-5.7	3.10	**0.50**	-4.6	2.50
EthioShed13	**0.4**	17.5	5.77	0.33	**-5.0**	3.97	0.29	-7.5	4.6	0.32	-6.4	4.15	0.37	-6.3	**3.90**
EthioShed14	**0.51**	**0.1**	**2.72**	0.43	-11.4	4.8	0.41	-15.8	6.17	0.38	-13.1	5.28	0.47	-13.5	5.20
EthioShed15	0.22	**3.0**	**3.1**	0.26	-6.3	3.9	0.3	-9.8	3.9	0.14	-10.2	4.5	0.27	-8.8	3.73
EthioShed16	**0.4**	**-3.1**	**3.45**	0.23	-12.7	5.1	0.25	-19.4	6.4	0.24	-15.2	5.45	0.30	-15.8	5.43
EthioShed17	**0.62**	5.2	**2.3**	0.58	**-3.6**	2.92	0.45	-7.8	3.2	0.53	-7.6	3.31	0.61	-6.4	2.66
KenShed1	**0.59**	9.6	3.2	0.39	4.6	3.03	0.37	**0.9**	2.94	0.34	2.3	2.85	0.46	2.6	**2.46**
KenShed2	**0.65**	-7.3	**2.62**	0.48	**-7.1**	3.02	0.4	-17.2	4.97	0.41	-11.8	3.83	0.53	-12.1	3.62
TanzShed1	**0.66**	**-5.5**	**3.11**	0.56	-9.2	4.16	0.39	-11.4	4.82	0.48	-11.1	4.58	0.58	-10.6	4.20
TanzShed2	**0.48**	**-4.1**	**2.8**	0.35	-14	4.9	0.22	-13.9	5.03	0.35	16.4	5.4	0.40	-14.8	4.90

Table ~~5~~6: Statistical evaluation of daily T-min retrieved from climate model and reanalysis-based products against ground observations over the period of 1983–2005 for 21 validation areas of East Africa. For ease of comparison, only selected statistical estimators are given in the table. Best fit is indicated in bold.

Validation areas	ORH			HadGEM2~~Had~~			GFDL			MPI			RCMs		
	CC	Rbias	RMSE	CC	Rbias	RMSE	CC	Rbias	RMSE	CC	Rbias	RMSE	CC	Rbias	RMSE
EthioShed1	**0.54**	7.1	**1.76**	0.45	12.8	2.55	0.37	**3.7**	2.44	0.4	10.4	2.32	0.51	9.0	1.97
EthioShed2	**0.77**	-11.3	**2.11**	0.59	**-6**	2.2	0.54	-18.7	3.27	0.58	-7.1	2.28	0.67	-10.7	2.14
EthioShed3	**0.65**	6.8	**2.12**	0.55	15.5	2.71	0.52	**4.9**	2.31	0.51	13.3	2.58	0.62	11.2	2.20
EthioShed4	**0.76**	12.1	**2.50**	0.60	-12.3	3.01	0.45	-26.8	4.71	0.61	**-11.6**	3.07	0.62	-16.9	3.28
EthioShed5	**0.45**	-10.9	2.65	0.28	6.9	2.28	0.31	-3.9	2.29	0.22	3.9	2.15	0.36	**2.3**	**1.78**
EthioShed6	**0.69**	-10.4	**1.9**	0.53	16.5	2.38	0.47	**6.7**	2.38	0.49	15.9	2.42	0.61	13.1	2.03
EthioShed7	**0.63**	-7.6	**2.01**	0.23	9.4	2.60	0.26	**-0.5**	2.87	0.29	6.4	2.30	0.35	5.1	2.03
EthioShed8	**0.33**	**-0.1**	**1.65**	0.24	16.7	3.08	0.21	8.6	2.78	0.15	12	2.6	0.27	12.4	2.46
EthioShed9	**0.68**	7.5	**2.84**	0.64	**-2.1**	2.87	0.59	-8.0	3.82	0.58	-1.8	3.13	0.65	-4.0	2.91
EthioShed10	**0.67**	16.2	2.58	0.50	9.4	2.46	0.38	**-3.1**	2.66	0.50	8.8	2.51	0.54	5.0	**2.13**
EthioShed11	**0.36**	-17.2	3.22	0.18	17.8	3.48	0.24	**13.8**	3.20	0.16	15.8	3.28	0.27	15.8	**3.10**
EthioShed12	**0.46**	-6.6	2.47	0.41	-3.8	2.40	0.34	-6.6	2.9	0.39	**-1.9**	2.26	0.45	-4.1	**2.21**
EthioShed13	**0.57**	31.2	4.77	0.54	2.7	2.76	0.46	-8.9	3.42	0.54	2.3	2.86	0.56	**-1.3**	**2.67**
EthioShed14	**0.72**	**4.6**	**2.68**	0.61	-5.6	3.27	0.55	-16.3	4.62	0.59	-5.5	3.32	0.63	-9.2	3.40
EthioShed15	**0.62**	-1.8	**2.16**	0.41	9.8	2.61	0.44	**0.5**	2.41	0.36	6.7	2.54	0.51	5.7	2.19
EthioShed16	**0.50**	-8.2	**3.45**	0.42	-7.7	3.7	0.31	-23.1	4.98	0.42	**-7.1**	3.66	0.44	-12.7	3.77
EthioShed17	**0.61**	**7.1**	**2.17**	0.43	19.7	2.96	0.44	9.0	2.44	0.36	17.1	2.87	0.53	15.3	2.46
KenShed1	**0.52**	14.8	2.66	0.31	9.0	2.44	0.17	**3.2**	2.46	0.3	10.4	2.52	0.34	7.5	**2.18**
KenShed2	**0.40**	-21.3	3.26	0.25	-18.1	3.15	0.25	-24.6	4.0	0.32	**-16.1**	**2.88**	0.35	-19.6	3.15
TanzShed1	**0.53**	**-12.0**	**3.12**	0.44	-15	3.69	0.38	-18.9	4.23	0.44	-15.3	3.71	0.5	-16.2	3.72
TanzShed2	0.51	**-16.2**	**3.87**	0.58	-17.3	3.9	0.46	-16.8	4.04	0.58	-18.5	4.16	**0.61**	-17.5	3.93

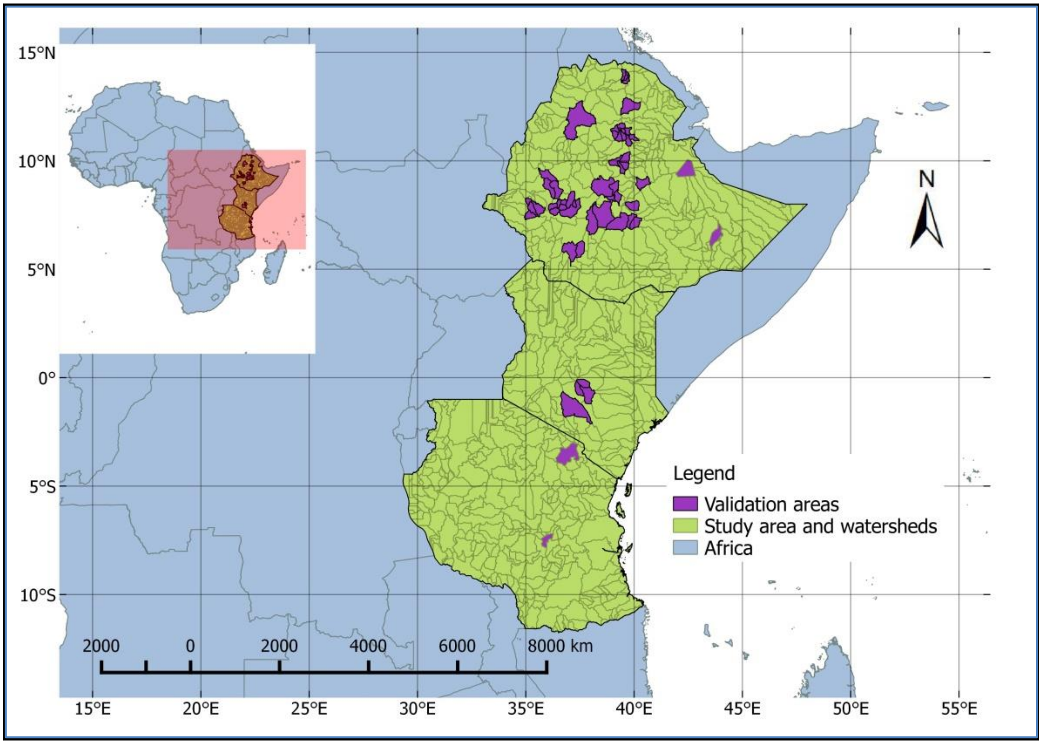

Figure 1: Map of Africa and study regions (Ethiopia, Kenya, and Tanzania) with data validation areas (EthioShed1–17, KenShed1&2, and TanzShed1&2). The basins are retrieved from the WaterBase global data portal (http://www.waterbase.org/).

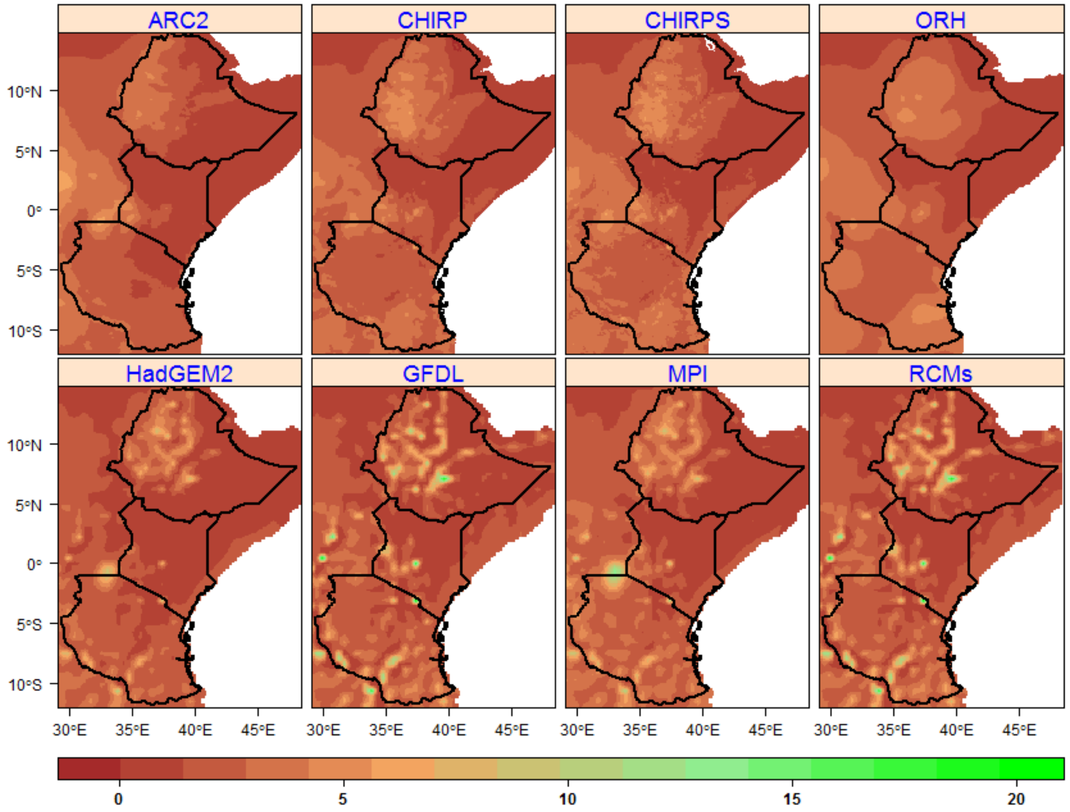

Figure 2: Average daily rainfall (mm day^{-1}) maps of East Africa retrieved from ARC2, CHIRP, CHIRPS, ORH, RCM, and RCMs for the study period 1983–2005. All the maps are given in a 0.05° spatial resolution.

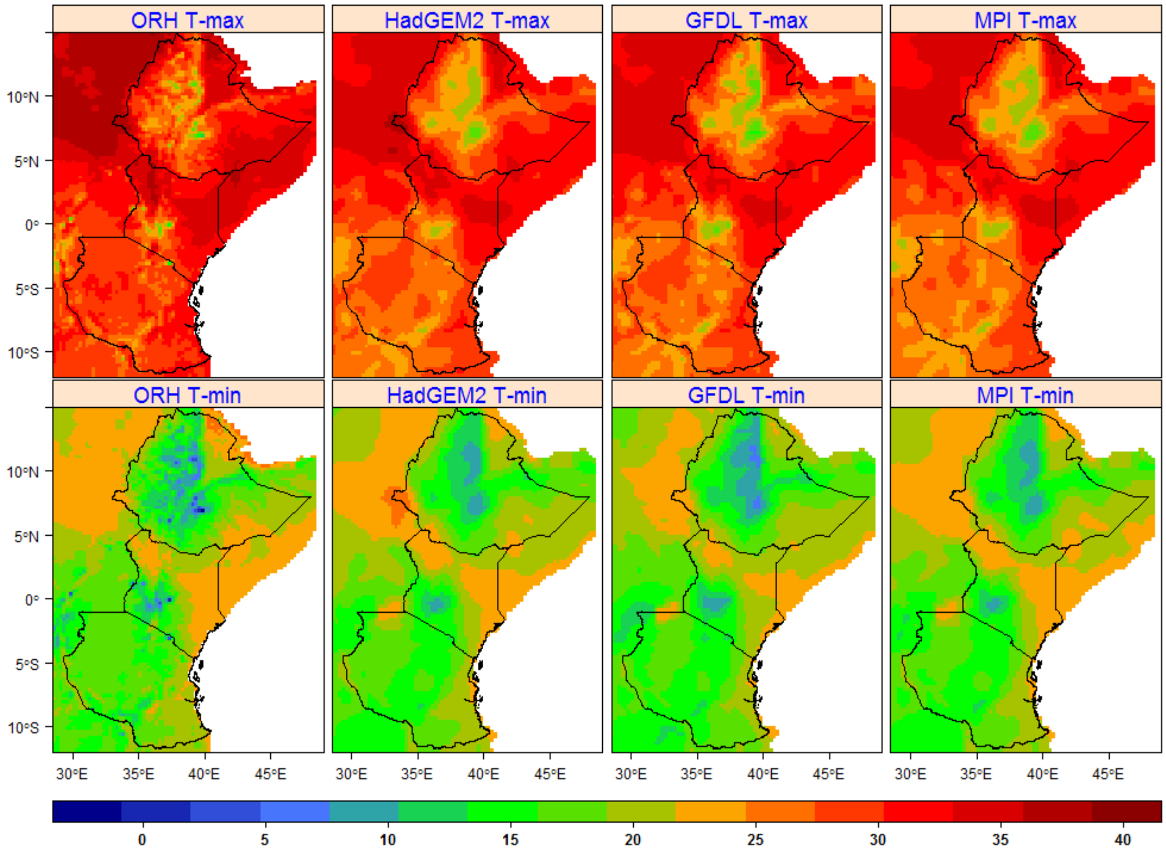

Figure 3: Maps of average daily T-max and T-min (°C) for East Africa generated from ORH and RCMs for the study period 1983–2005. All the maps are given in a 0.1° spatial resolution.

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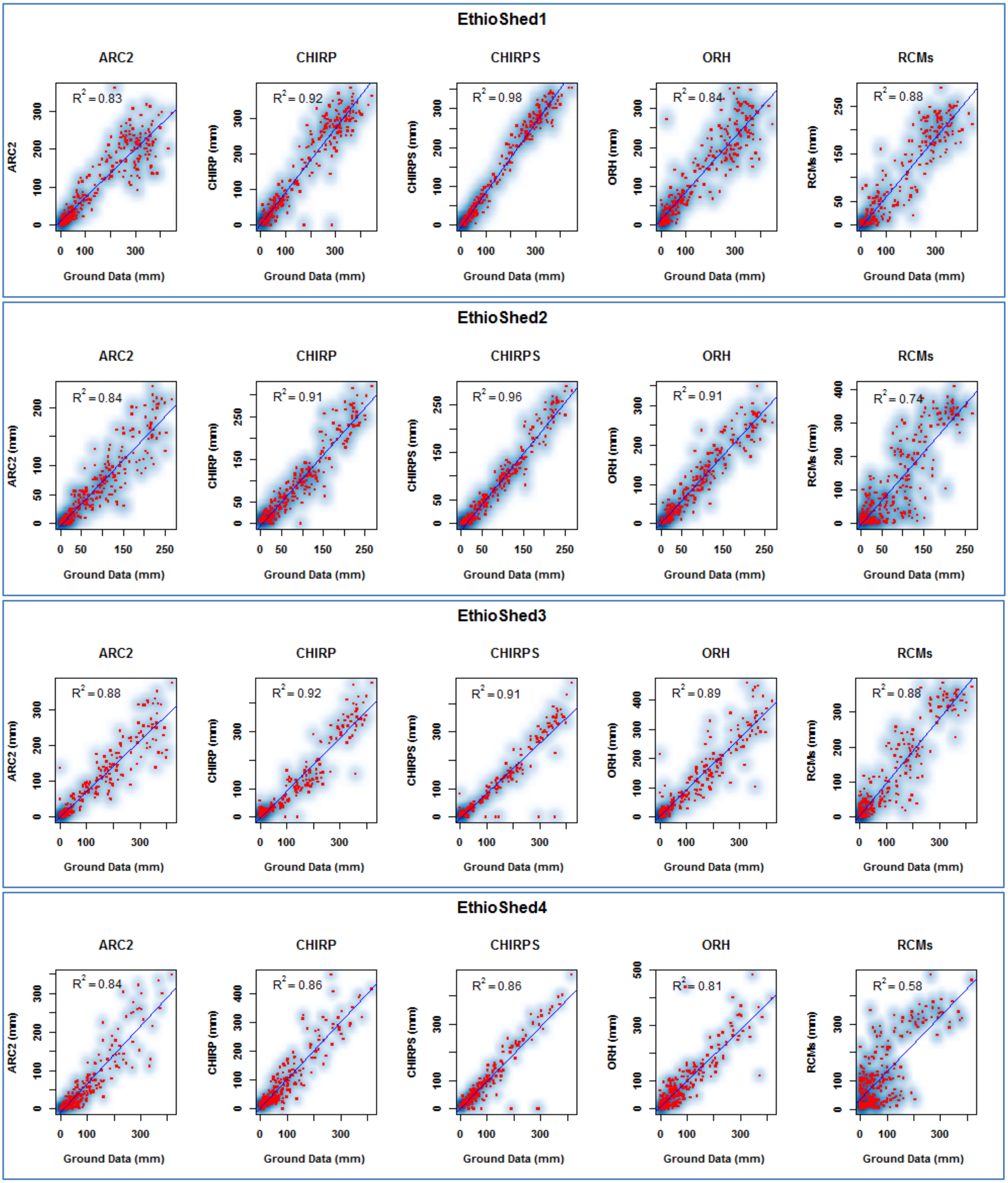
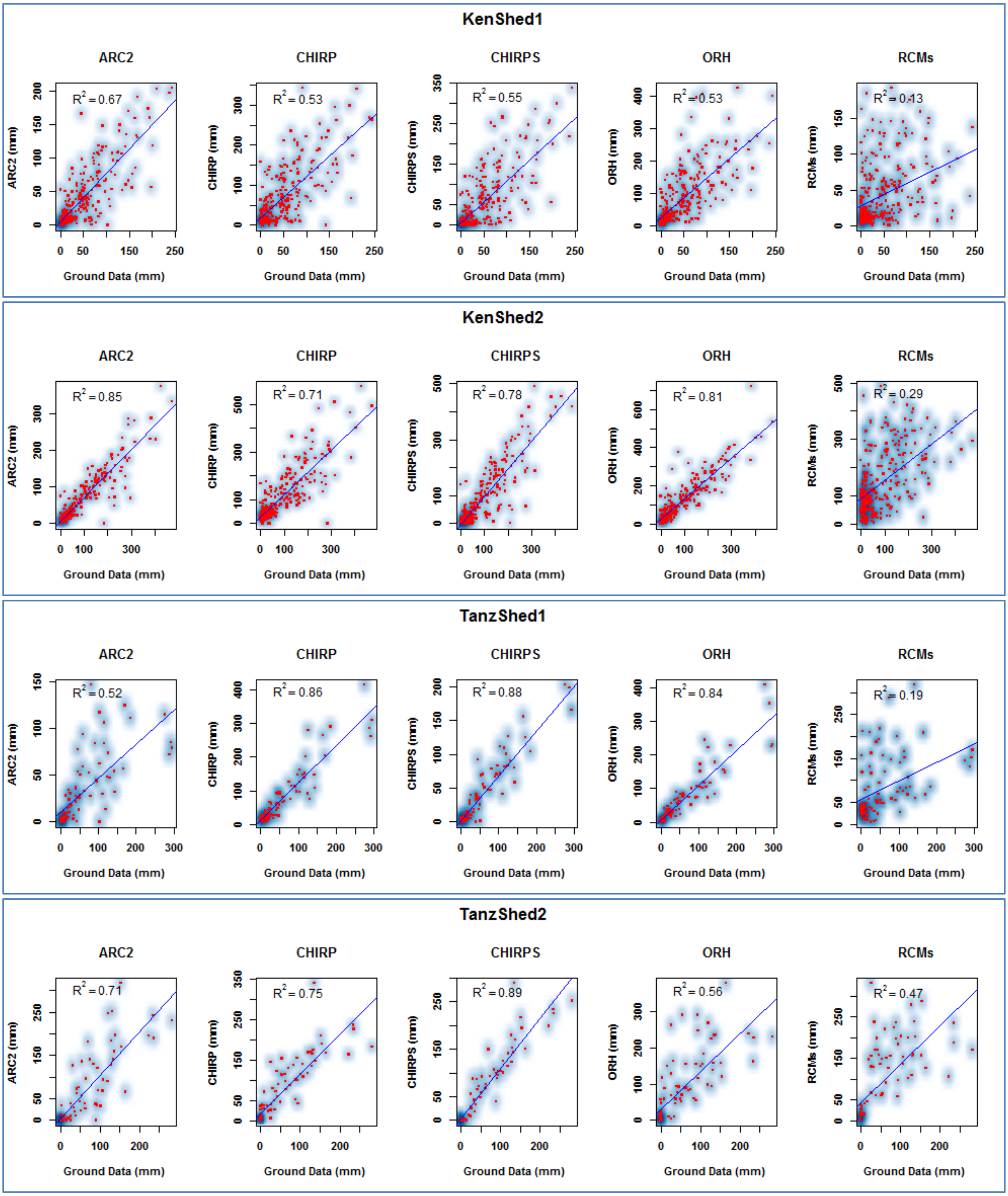
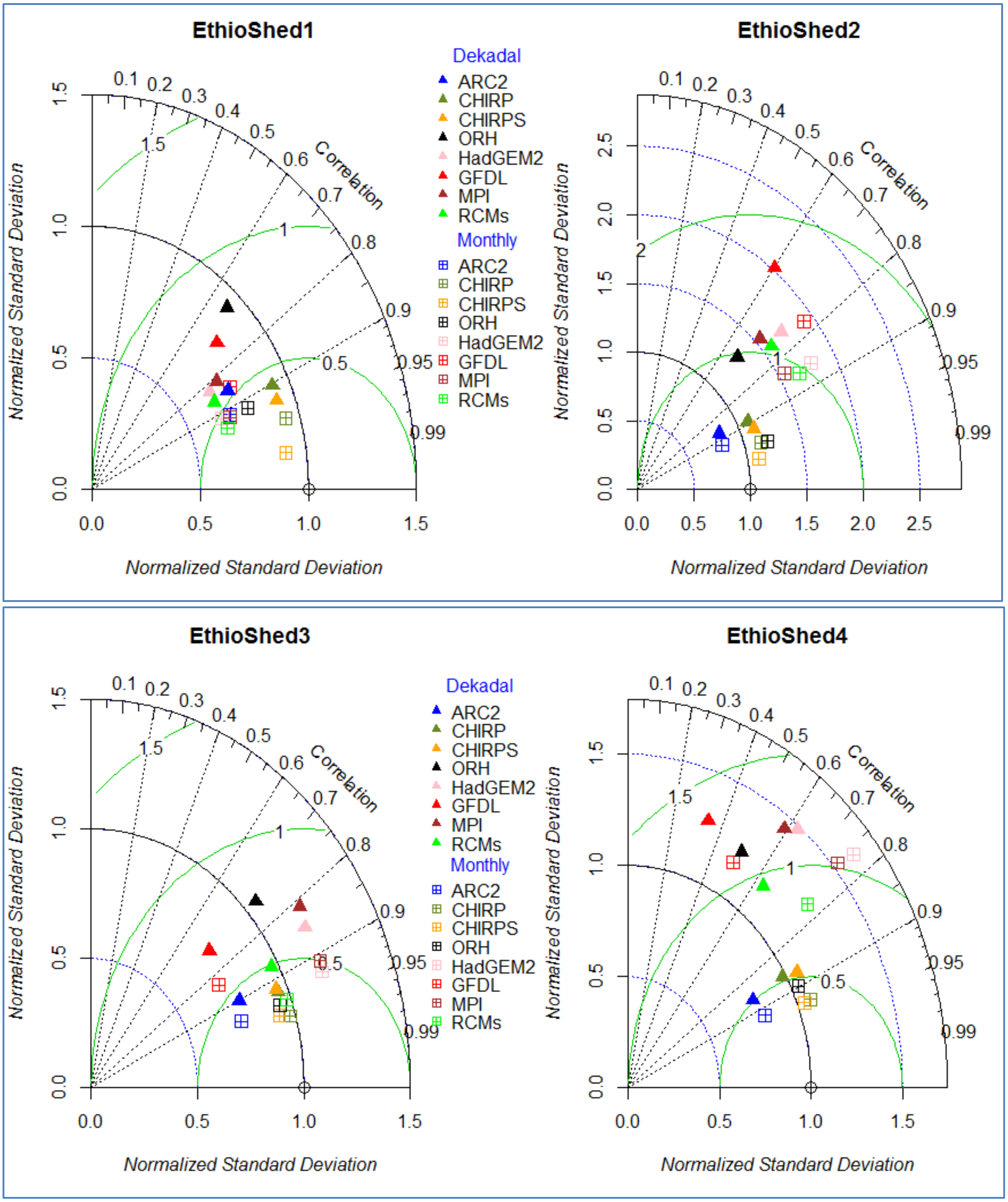

EthioShed1
ARC2
CHIRP
CHIRPS
ORH
RCMs
R² = 0.83
R² = 0.92
R² = 0.98
R² = 0.84
R² = 0.88
EthioShed2
ARC2
CHIRP
CHIRPS
ORH
RCMs
R² = 0.84
R² = 0.91
R² = 0.96
R² = 0.91
R² = 0.74
EthioShed3
ARC2
CHIRP
CHIRPS
ORH
RCMs
R² = 0.88
R² = 0.92
R² = 0.91
R² = 0.89
R² = 0.88
EthioShed4
ARC2
CHIRP
CHIRPS
ORH
RCMs
R² = 0.84
R² = 0.86
R² = 0.86
R² = 0.81
R² = 0.58
ARC2 (mm)
CHIRP (mm)
CHIRPS (mm)
ORH (mm)
RCMs (mm)
Ground Data (mm)



KenShed1
ARC2
CHIRP
CHIRPS
ORH
RCMs
R² = 0.67
R² = 0.53
R² = 0.55
R² = 0.53
R² = 0.13
ARC2 (mm)
CHIRP (mm)
CHIRPS (mm)
ORH (mm)
RCMs (mm)
Ground Data (mm)
KenShed2
R² = 0.85
R² = 0.71
R² = 0.78
R² = 0.81
R² = 0.29
TanzShed1
R² = 0.52
R² = 0.86
R² = 0.88
R² = 0.84
R² = 0.19
TanzShed2
R² = 0.71
R² = 0.75
R² = 0.89
R² = 0.56
R² = 0.47

Figure 4: Scatter plots of monthly rainfall for ARC2, CHIRP, CHIRPS, ORH, and RCMs for eight validation areas covering the period of 1983–2005 and aggregated from daily data. Shaded area displays the data density around the regression line.



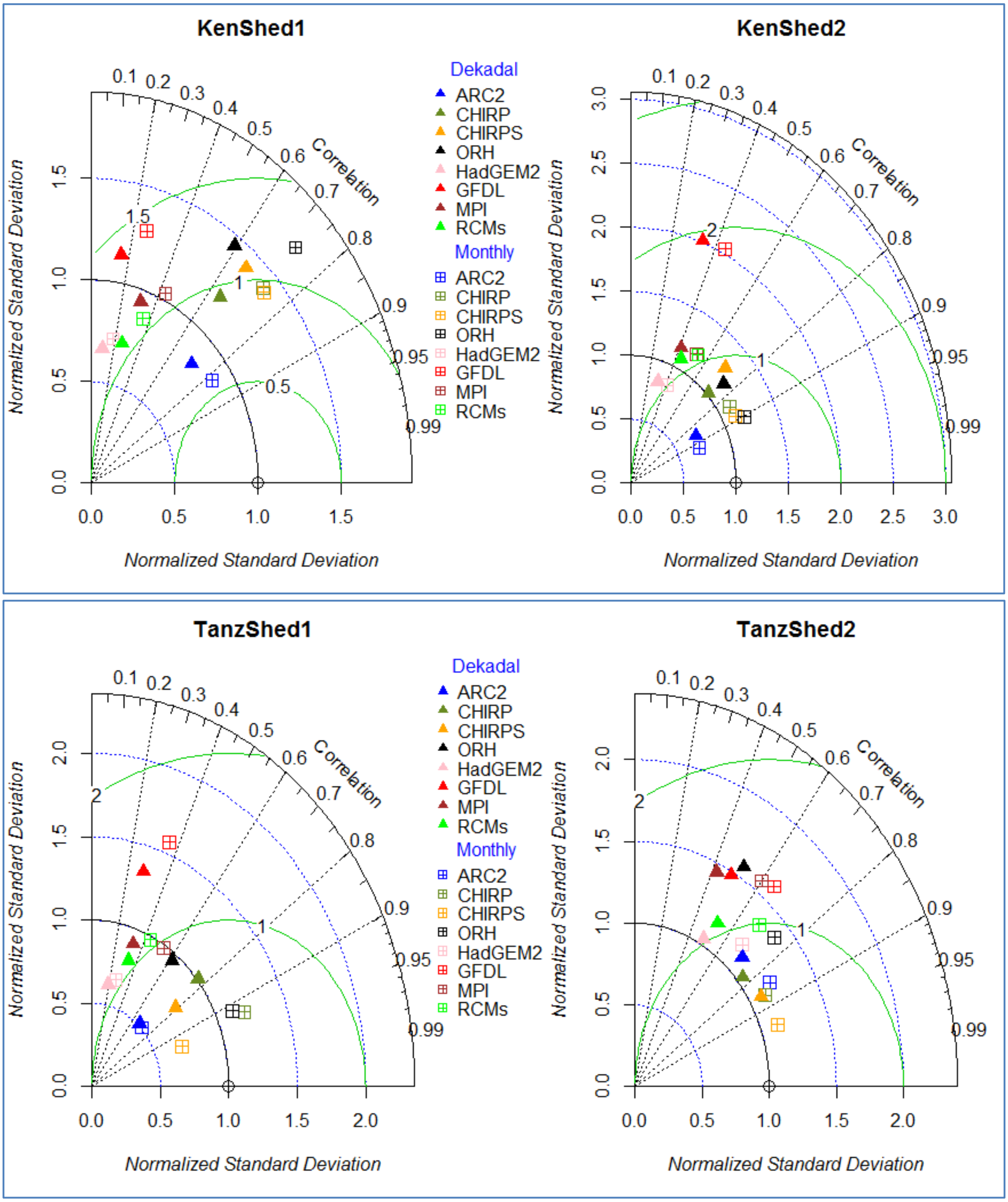
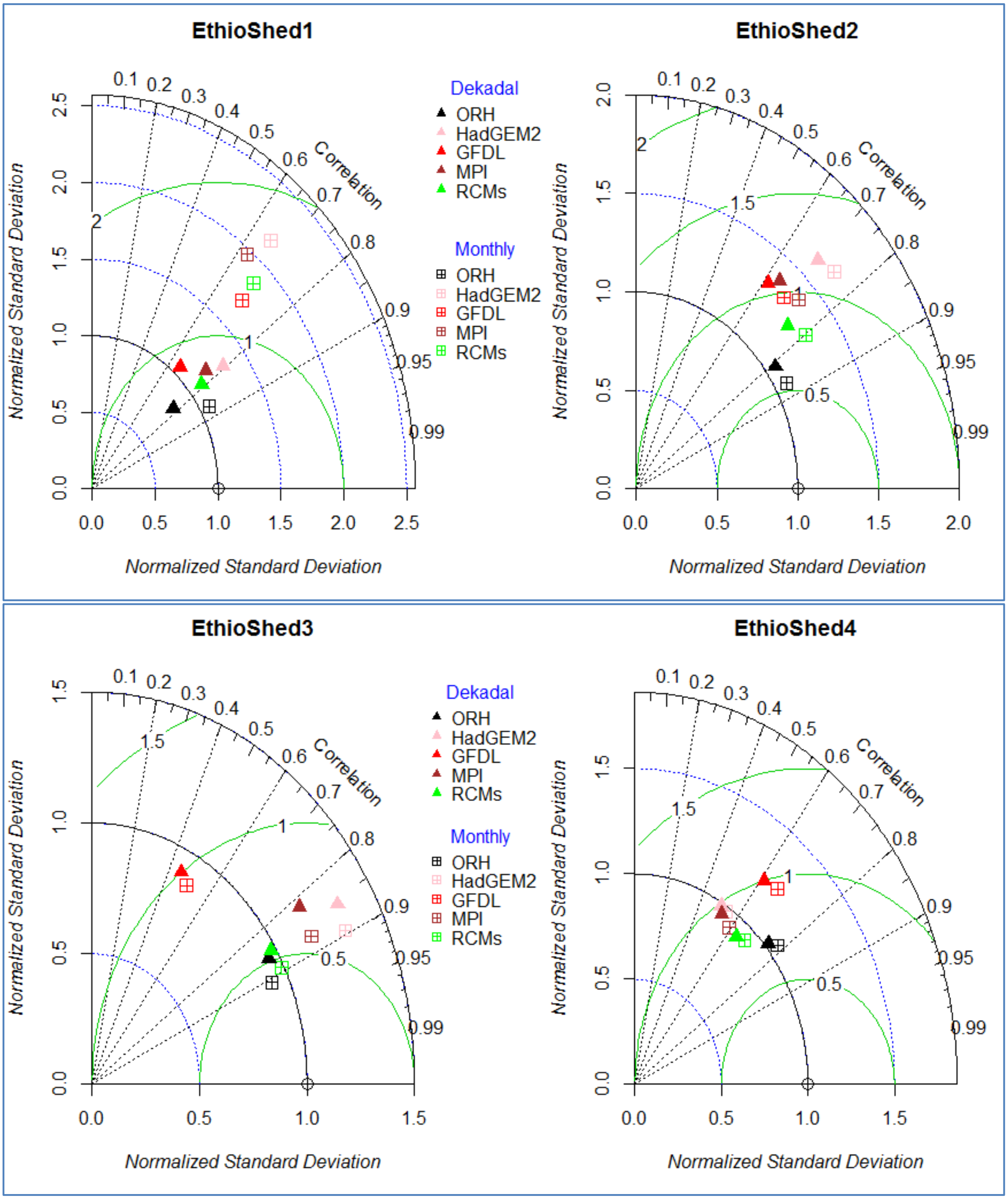


Figure 5: Taylor diagram displaying the agreement between ground observation and synthesized dekadal and monthly rainfall over eight validation areas of Ethiopia, Kenya, and Tanzania covering the period of 1983– 2005.


EthioShed1
EthioShed2
EthioShed3
EthioShed4
Dekadal
ORH
HadGEM2
GFDL
MPI
RCMs
Monthly
ORH
HadGEM2
GFDL
MPI
RCMs
Correlation
Normalized Standard Deviation

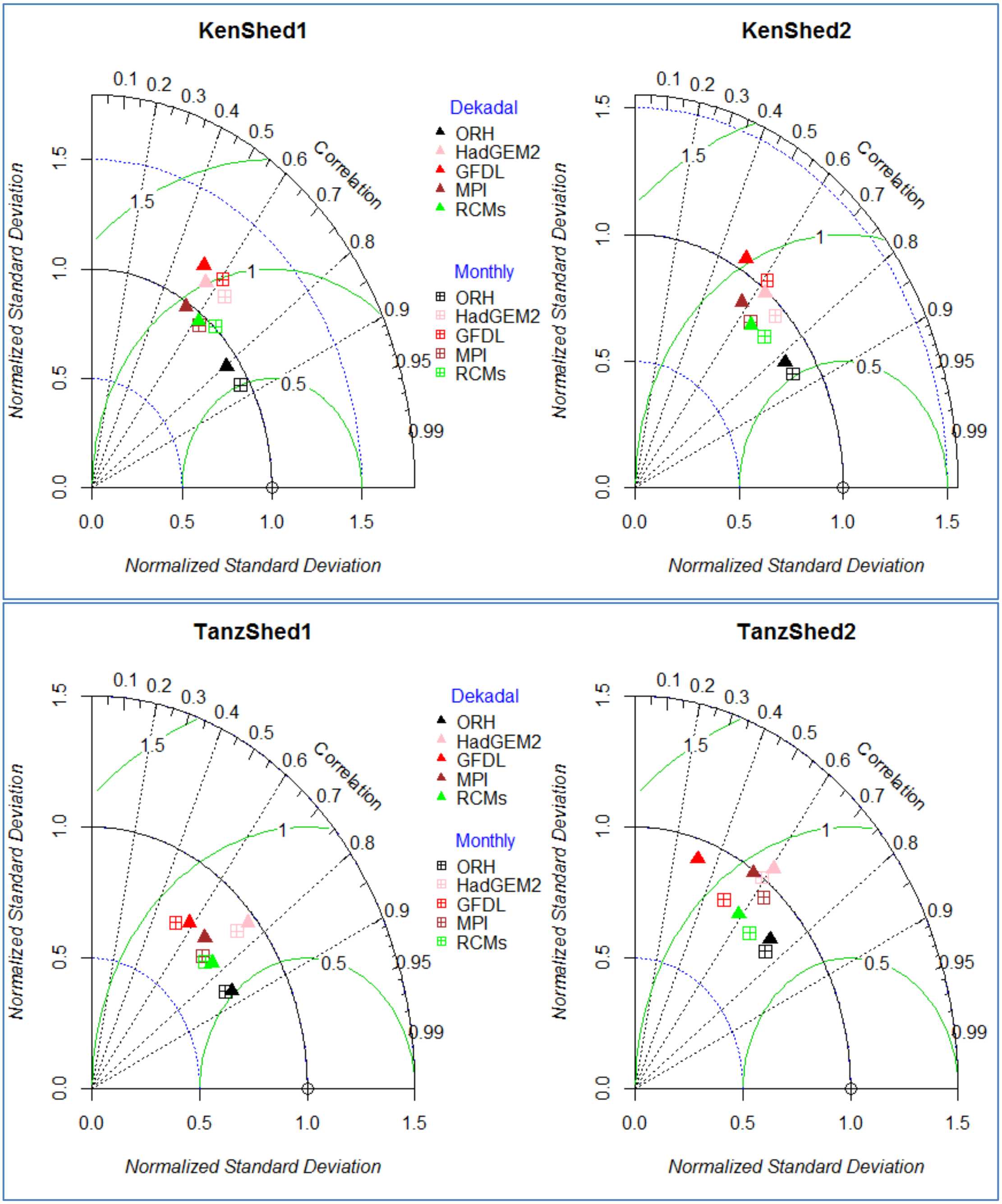
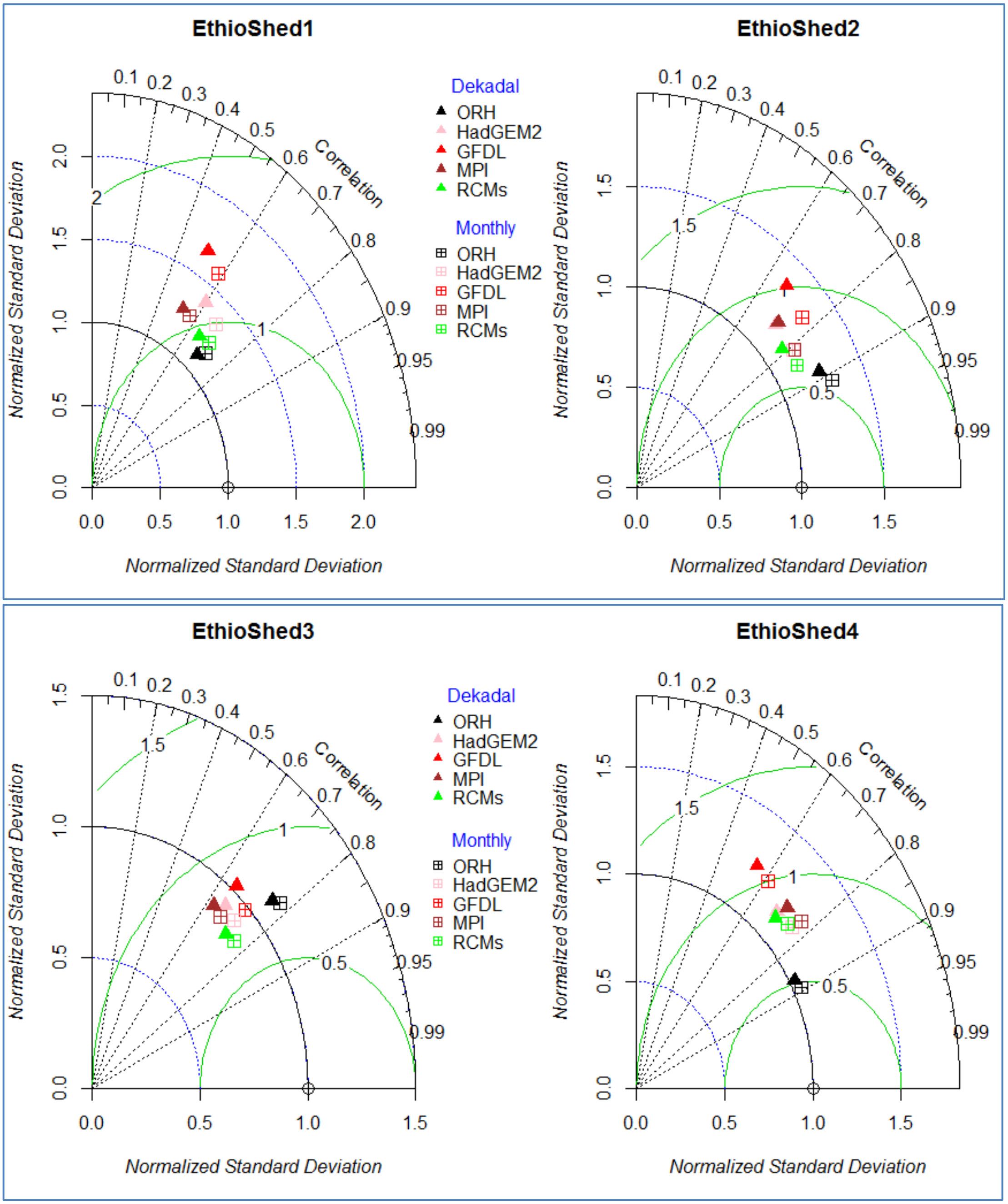


Figure 6: Taylor diagram displaying the agreement between ground observation and synthesized dekadal and monthly T-max over the eight validation areas of Ethiopia, Kenya, and Tanzania covering the period of 1983–2005.


EthioShed1
EthioShed2
EthioShed3
EthioShed4
Dekadal
ORH
HadGEM2
GFDL
MPI
RCMs
Monthly
ORH
HadGEM2
GFDL
MPI
RCMs
Correlation
Normalized Standard Deviation
Normalized Standard Deviation

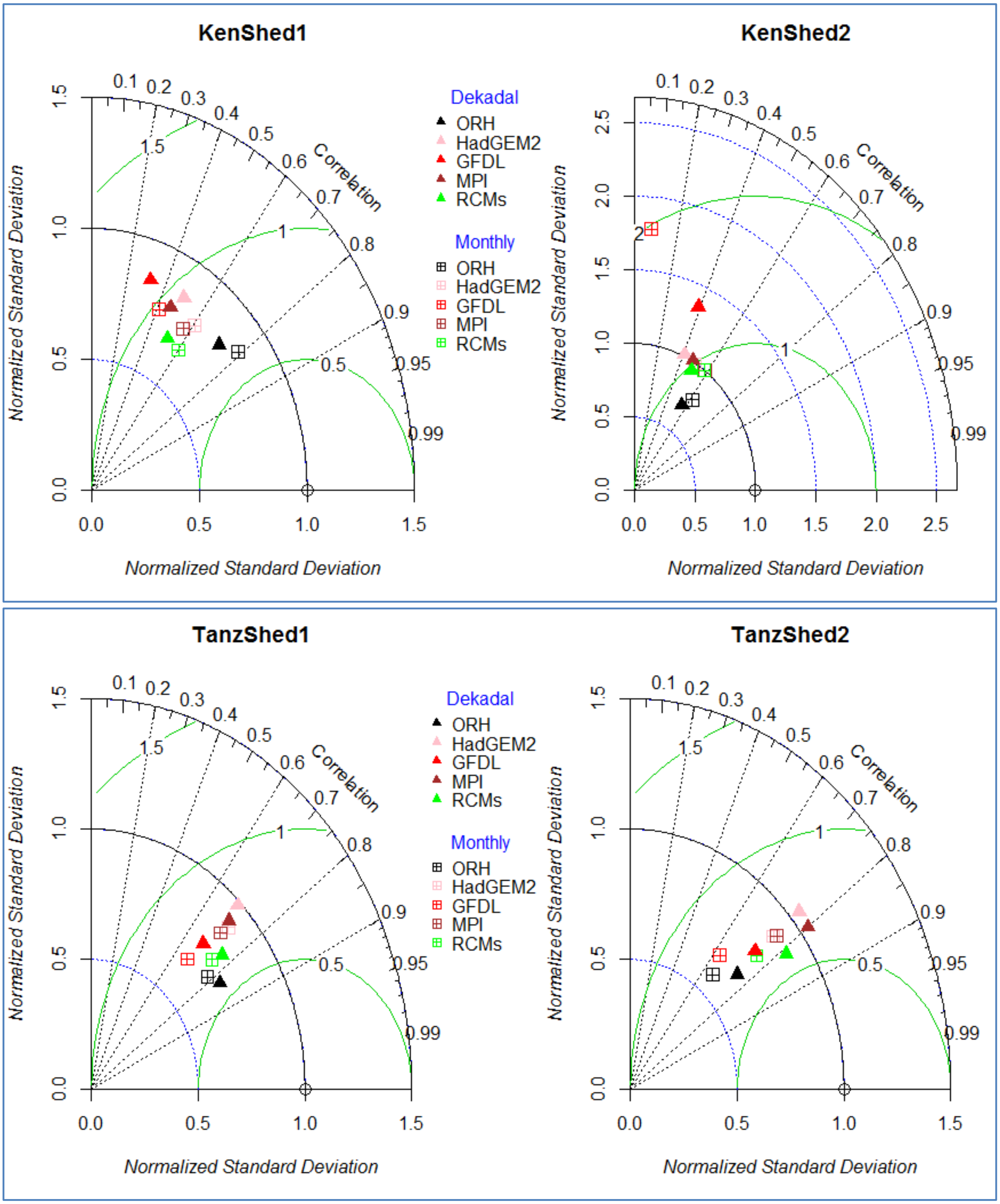


Figure 7: Taylor diagram displaying the agreement between ground observation and synthesized dekadal and monthly T-min over eight validation areas of Ethiopia, Kenya, and Tanzania covering the period of 1983– 2005.

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Acknowledgements

We would like to thank the National Meteorological Agency (NMA) of Ethiopia for providing adequate data for the study and the World Meteorological Organization (WMO) representative for Eastern and Southern Africa for their kind support in data collection. We would also like to thank the Graduate Academy of Technische Universität Dresden (TU Dresden) for its financial support during the study period.

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